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Computer-Assisted Troubleshooting for Efficient Off-board Diagnosis

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ABSTRACT

This licentiate thesis considers computer-assisted troubleshooting of complex products such as heavy trucks. The troubleshooting task is to find and repair all faulty components in a malfunctioning system. This is done by performing actions to gather more information regarding which faults there can be or to repair components that are suspected to be faulty. The expected cost of the performed actions should be as low as possible.

The work described in this thesis contributes to solving the troubleshooting task in such a way that a good trade-off between computation time and solution quality can be made. A framework for troubleshooting is developed where the system is diagnosed using non-stationary dynamic Bayesian networks and the decisions of which actions to perform are made using a new planning algorithm for Stochastic Shortest Path Problems called Iterative Bounding LAO*.

It is shown how the troubleshooting problem can be converted into a Stochastic Shortest Path problem so that it can be efficiently solved using general algorithms such as Iterative Bounding LAO*. New and improved search heuristics for solving the troubleshooting problem by searching are also presented in this thesis.

The methods presented in this thesis are evaluated in a case study of an auxiliary hydraulic braking system of a modern truck. The evaluation shows that the new algorithm Iterative Bounding LAO* creates troubleshooting plans with a lower expected cost faster than existing state-of-the-art algorithms in the literature. The case study shows that the troubleshooting framework can be applied to systems from the heavy vehicles domain.

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Contents

Part I

Introduction

1 Background

Troubleshooting is the process of locating the cause of a problem in a system and resolving it. This can be particularly difficult in automotive systems such as cars, buses, and trucks. Modern vehicles are complex products consisting of many components that interact in intricate ways. When a fault occurs in such a system, it may manifest itself in many different ways and a skilled mechanic is required to find it. A modern mechanic must therefore have an understanding of the mechanical and thermodynamic processes in for example the engine and exhaust system as well as the electrical and logical processes in the control units. Every year, the next generation of vehicles is more complex than the last one, and the troubleshooting task becomes more difficult for the mechanic.

This thesis is about computer-assisted troubleshooting of automotive systems. In computer-assisted troubleshooting, the person performing the troubleshooting is assisted by a computer that recommends actions that can be taken to locate and resolve the problem. To do this, the computer needs to be able to reason about the object that we troubleshoot and to foresee the consequences of performed actions. Theoretical methods of doing this are developed in this thesis. Troubleshooting heavy commercial vehicles such as trucks and buses is of particular interest.

1.1 Why Computer-Assisted Troubleshooting?

The trend in the automotive industry is that vehicles are rapidly becoming more and more complex. Increased requirements on safety and environmental performance have led to many recent advances, especially in the engine, braking system and exhaust system [14, 70, 83]. These new systems are increasing in complexity. For example, in addition to conventional brakes, a truck may have an exhaust brake and a hydraulic braking system. To reduce emissions and meet regulations, the exhaust gases can be led back through the engine for more efficient combustion [82] or urea can be mixed with the exhaust gases to reduce nitrogen emissions. Such systems require additional control and since the early 1990s, the number of Electronic Control Units (ECU:s) and sensors in vehicles has increased more than tenfold [49].

With this trend towards more complex vehicles, it is becoming more difficult, even for an experienced workshop mechanic, to have an intuitive understanding of a vehicle's behavior. A misunderstanding of the vehicle's behavior can for example lead to replacing expensive ECU:s even if they are not responsible for the fault at hand. Faults may depend on a combination of electrical, logical, mechanical, thermodynamic, and chemical processes. For example, suppose the automatic climate control system (ACC) fails to produce the correct temperature in the cab. This can be caused by a fault in the ECU controlling the ACC, but it can also be caused by a damaged temperature sensor used by the ECU. The mechanic may then replace the ECU because it is quicker. However, since this is an expensive component it could be better to try replacing the temperature sensor first. In this case, the mechanic could be helped by a system for computer aided troubleshooting that provides decision support by pointing out suspected faults and recommending suitable actions the mechanic may take.

Computers are already used as tools in the service workshops. In particular, they are used to read out diagnostic messages from the ECU:s in a vehicle and to set parameters such as fuel injection times and control strategies. The diagnostic messages, Diagnostic Trouble Codes (DTC:s), come from an On-Board Diagnosis (OBD) system that runs on the vehicle. Ideally, each DTC points out a component or part of the vehicle that may not function properly. However, often it is the case that a single fault may generate multiple DTC:s and that the same DTC can be generated by several faults. The OBD is primarily designed to detect if a failure that is safety-critical, affects environmental performance, or may immobilize the vehicle has occurred. This information is helpful but not always specific enough to locate exactly which fault caused the failure. The mechanic must therefore also gather information from other sources such as the driver or visual inspections. In order for a computer-assisted troubleshooting system to be helpful for the mechanic, it must also be able to consider all of these information sources.

Another important aspect of troubleshooting is the time required to resolve a problem. Trucks are commercial vehicles. When they break down it is particularly important that they are back in service as soon as possible so that they can continue to generate income for the fleet owner. Therefore, the time required to find the correct faults must be minimized. Many retailers now sell repair and maintenance contracts which let the fleet owner pay a fixed price for all repair and maintenance needs [45, 72, 84]. A computer-assisted troubleshooting system that could reduce the total expected cost and time of maintenance and repair would lead to large savings for the fleet owner due to time savings and for the retailer because of reduced expenses.

1.2 Problem Formulation

We will generalize from heavy vehicles and look upon the object that we troubleshoot as a *system* consisting of *components*. Some of these components may be faulty and should then be repaired. We do not know which components that are faulty. However, we can make observations from which we can draw conclusions about the status of the components. The *troubleshooting task* is to make the system fault-free by performing actions on it that gather more information or make repairs. The system is said to be fault-free when none of the components which constitute the system are faulty. We want to solve the troubleshooting task at the smallest possible cost where the cost is measured in time and money.

To do this, we want to use a system for computer-assisted troubleshooting, called a *troubleshooter*, that receives observations from the outside world and outputs recommendations of what actions should be performed to find and fix the problem. The user of the troubleshooter then performs the actions on the system that is troubleshot and returns any feedback to the troubleshooter.

The troubleshooter uses a *model* of the system to estimate the probability that the system is fault-free given the available information. When this estimated probability is 1.0, the troubleshooter considers the system to be fault-free. This is the *termination condition*. When the termination condition holds, the troubleshooting session is ended. The troubleshooter must generate a sequence of recommendations that eventually results in a situation where the termination condition holds. If the troubleshooter is correct when the termination condition holds, i.e. the system really is fault-free, the troubleshooter will be successful in solving the troubleshooting task.

When the system to troubleshoot is a truck, the user would be a mechanic.

The observations can consist of information regarding the type of the truck, operational statistics such as mileage, a problem description from the customer, or feedback from the mechanic regarding what actions have been performed and what has been seen. The output from the troubleshooter could consist of requests for additional information or recommendations to perform certain workshop tests or to replace a certain component.

1.2.1 Performance Measures

Any sequence of actions that solves the troubleshooting task does not necessarily have sufficient quality to be considered good troubleshooting. Therefore we will need some performance measures for troubleshooting. For example, one could make sure that the system is fault-free by replacing every single component. While this would certainly solve the problem, doing so would be very time-consuming and expensive.

One interesting performance measure is the cost of solving the troubleshooting task. This is the *cost of repair* and we will define it as the sum of the costs of all actions performed until the termination condition holds. However, depending on the outcome of information-gathering actions we may want to perform different actions. The outcomes of these information-gathering actions are not known in advance. Therefore, the *expectation* of the cost of repair given the currently available information is a more suitable performance measure. This is the *expected cost of repair* (ECR). If the ECR is minimal, then the average cost of using the troubleshooter is as low as possible in the long run. Then troubleshooting is said to be optimal.

For large systems, the problem of determining what actions to perform for optimal troubleshooting is computationally intractable [62]. Then another interesting performance measure is the time required to compute the next action to be performed. If the next action to perform is computed while the user is waiting, the computation time will contribute to the cost of repair. The computation time has to be traded off with the ECR because investing more time in the computations generally leads to a reduced ECR. Being able to estimate the quality of the current decision and give a bound on its relative cost difference to the optimal ECR can be vital in doing this trade-off.

1.3 Solution Methods

A common approach when solving the troubleshooting task has been to divide the problem into two parts: the *diagnosis problem* and the *decision problem* [16, 27, 33, 42, 79, 90]. First the troubleshooter finds what could possibly be wrong given all information currently available, and then it decides which action should be performed next.

In Section 1.3.1, we will first present some common variants of the diagnosis problem that exist in the literature. These problems have been studied extensively in the literature and we will describe some of the more approaches. The approaches vary in how the system is modeled and what the purpose of the diagnosis is. In Section 1.3.2, we will present previous work on how the decision problem can be solved.

1.3.1 The Diagnosis Problem

A *diagnosis* is a specification of which components are faulty and non-faulty. The diagnosis problem is the problem of finding which is the diagnosis or which are the possible diagnoses for the system being diagnosed given the currently available information. Diagnosis is generally based on a model that describes the behavior of a system, where the system is seen as a set of components [7, 15, 16, 26, 33, 56, 61, 65, 77]. This can be a model of the physical aspects of the system, where each component's behavior is modeled explicitly using for example universal laws of physics and wiring diagrams [7, 77]. It can also be a black box model which is learned from training data [69, 91]. Then no explicit representation of how the system works is required.

The purpose of diagnosis can be fault detection or fault isolation. For *fault detection*, we are satisfied with being able to discriminate the case where no component is faulty from from the case where at least one component is faulty. Often it is important that the detection can be made as soon as possible after the fault has occurred [35]. For *fault isolation*, we want to know more specifically which diagnoses are possible. Sometimes it is not possible to isolate a single candidate and the output from diagnosis can be all possible diagnoses [18], a subset of the possible diagnoses [26], or a probability distribution over all possible diagnoses [56, 81].

Consistency-Based Approach

A formal theory for consistency-based diagnosis using logical models is first described by Reiter [61]. Each component can be in one of two or more behavioral modes of which one is nominal behavior and the others are faulty behaviors. The system model is a set of logical sentences describing how the components' inputs and outputs relate to each other during nominal and faulty behavior. A possible diagnosis is any assignment of the components' behavioral modes that is consistent with the system model and the information available in the form of observations.

The set of all possible diagnoses can be immensely large. However, it can be characterized by a smaller set of diagnoses with minimal cardinality if faulty behavior is unspecified [15]. If faulty behavior is modeled explicitly [18] or if components may have more than two behavioral modes [17], all possible diagnoses can be represented by a set of partial diagnoses.

Frameworks for diagnosis such as the General Diagnostic Engine (GDE) [16] or Lydia [26] can compute such sets of characterizing diagnoses either exactly or approximately. Consistency-based diagnosis using logical models have been shown to perform well for isolating faults in static systems such as electronic circuits [41].

Control-Theoretic Approach

In the control-theoretic approach, the system is modeled with Differential Algebraic Equations (DAE) [7, 77]. As many laws of physics can be described using differential equations, precise physical models of dynamical systems can be created with the DAE:s. Each DAE is associated with a component and typically the DAE:s describe the components' behavior in the non-faulty case [7]. When the system of DAE:s is analytically redundant, i.e. there are more equations than unknowns, it is possible to extract diagnostic information [77]. If an equation can be removed so that the DAE becomes solvable, the component to which that equation belongs is a possible diagnosis.

These methods depend on accurate models and have been successful for fault detection in many real world applications [36, 63]. Recently efforts have been made to integrate methods for logical models with techniques traditionally used for fault detection in physical models [13, 44].

Data-Driven Methods

In data-driven methods, the model is learned from training data, instead of deriving it from explicit knowledge of the system's behavior. When large amounts of previously classified fault cases in similar systems are available, the data-driven methods can learn a function that maps observations to diagnoses. Such methods include Support Vector Machines, Neural Networks, and Case Based Reasoning (see e.g. [69], [43, 91], and [38] respectively).

Discrete Event Systems

For Discrete Event Systems (DES), the system to be diagnosed is modeled as a set of states that the system can be in together with the possible transitions the system can make between states. Some transitions may occur due to faults.

An observation on a DES gives the information that a certain transition has occurred. However, not all transitions give rise to an observation. The diagnosis task is to estimate which states the system has been in by monitoring the sequence of observations and to determine if any transitions have occurred that are due to faults. Approaches used for DES include Petri Nets [28] and state automata [55, 92].

Probabilistic Approaches

Probabilistic methods for diagnosis estimate the probability of a certain diagnosis being true. The model can be a pure probabilistic model such as a Bayesian Network (BN) that describes probabilistic dependencies between components and observations that can be made [39]. This model can for instance be derived from training data using data-driven methods [74] or from a model of the physical aspects of the system such as bond graphs [65]. It is also possible to combine learning techniques with the derivation of a BN from a physical model such as a set of differential algebraic equations [56]. Once a BN has been derived, it is possible to infer a posterior probability distribution over possible diagnoses given the observations.

Another technique is to use a logical model and consistency-based diagnosis to first find all diagnoses that are consistent with the model and then create the posterior distribution by assigning probabilities to the consistent diagnoses from a prior probability distribution [16]. For dynamic models where the behavioral mode of a component may change over time, techniques such as Kalman filters or particle filters can be used to obtain the posterior probability distribution over possible diagnoses [5, 81]. These methods are approximate and can often be more computationally efficient than Bayesian networks.

1.3.2 The Decision Problem

Once the troubleshooter knows which the possible diagnoses are, it should decide what to do next in order to take us closer to our goal of having all faults repaired. Actions can be taken to repair faults or to create more observations so that candidate diagnoses can be eliminated. There are different approaches to deciding which of these actions should be performed. For example, one decision strategy could be to choose the action that seems to take the longest step toward solving the troubleshooting task without considering what remains to do to completely solve the task [16, 33, 42, 79]. Another strategy could be to generate a complete plan for solving the task and then select the first action in this plan [4, 89]. It is also possible to make the decision based on previous experience of what decisions were taken in similar situations [43].

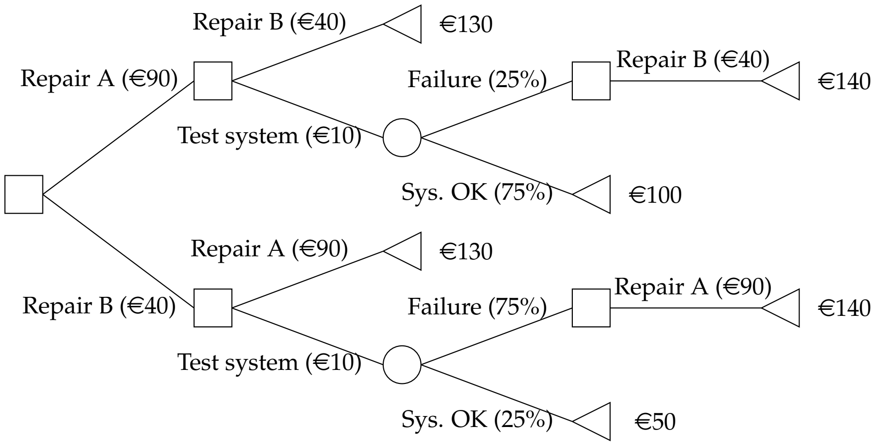


Figure 1.1: A decision tree for repairing two components A and B. Decision nodes are shown with squares, chance nodes are shown with circles, and end nodes are shown with triangles.

Decision Trees and Look-ahead Search

By considering every available action and every possible action outcome we can choose an action that leads to the most desirable outcome. This can be done using a decision tree [66]. An example of a decision tree is shown in Figure 1.1. The decision tree has three types of nodes: decision nodes, chance nodes, and end nodes. The nodes are joined by branches that correspond to either actions or action outcomes. In a decision node we can choose an action to perform, and we will follow the branch corresponding to the chosen action.. If the action can have one of multiple outcomes we reach a chance node. Depending on the outcome, we will follow a branch corresponding to that outcome from the chance node to another decision node or an end node. In the end nodes the final result is noted, e.g. "all suspected faults repaired at a cost of €130". A decision can be made by choosing the action that leads to the most favorable results. In the example in Figure 1.1, the most favorable decision would be to repair component A and then proceed by testing the system. This yields a 75% chance of a cost of €100 and a 25% chance of a cost of €140. This approach has been used for many types of decision problems in the area of economics and game theory [66].

For complex decision problems, though, the decision tree can become immensely large. One way to make the decision problem tractable is to prune the tree at a certain depth *k* and assign each pruned branch a value from a heuristic utility function. The decision is then the action that either minimizes or maximizes the expected utility in k steps. This is sometimes referred to as k-depth look-ahead search [68].

In de Kleer and Williams [16] the task is to find the fault in the system by sequentially performing observing actions. Here the possible diagnoses are inferred from the available observations using their General Diagnostic Engine and are assigned probabilities from a prior probability distribution as previously described in Section 1.3.1. The utility function is defined by the entropy of the probability distribution over the possible diagnoses. In information science, the entropy of a random variable is a measure of its uncertainty [30]. Here it is used to describe the remaining uncertainty regarding which is the true diagnosis among the set of possible diagnoses. Using only a fast one-step lookahead search, this method is remarkably efficient in finding action sequences that find the true diagnosis at a low expected cost. Sun and Weld [79] extend this method to also consider the cost of repairing the remaining possible faults in addition to the entropy.

In Heckerman et al. [33] and Langseth and Jensen [42], troubleshooting of printer systems is considered. A BN is used to model the system, the output from the diagnosis is a probability distribution over possible diagnoses, and the goal is to repair the system. By reducing the set of available actions and making some rather restricting assumptions regarding the system's behavior, the optimal expected cost of repair can efficiently be computed analytically. Even though these assumptions are not realistic for the printer system that they troubleshoot, the value for the optimal ECR when the assumptions hold is used as a utility function for a look-ahead search using the unreduced set of actions.

Planning-Based Methods

The troubleshooting problem can be formulated as a Markov Decision Process (MDP) or a Partially Observable MDP (POMDP) [4]. An MDP describes how stochastic transitions between states occur under the influence of actions. A natural way of modeling our problem is using states consisting of the diagnosis and the observations made so far. Since we know the observations made but do not know the diagnosis, such states are only partially observable and can be handled using a POMDP. We can also use states consisting of a *probability distribution* over possible diagnoses together with the observations made so far. Such states are more complex, but are fully observable and allow the troubleshooting problem to be modeled as an MDP.

A solution to an MDP or a POMDP is a function that maps states to actions called a *policy*. A policy describes a plan of actions that maximizes the expected reward or minimizes the expected cost. This is a well-studied area and there are many algorithms for solving (PO)MDP:s optimally. However, in the general case, solving (PO)MDP:s optimally is intractable for most non-trivial problems.

Anytime algorithms such as Learning Depth-First Search [8] or Real-Time Dynamic Programming [2] for MDPs and, for POMDPs, Point-Based Value Iteration [59] or Heuristic Search Value Iteration [75] provide a trade-off between computational efficiency and solution quality. These algorithms only explore parts of the state space and converge towards optimality as more computation time is available.

If a problem that can be modeled as a POMDP is a *shortest path POMDP*, then it can be more efficiently solved using methods for ordinary MDP:s such as RTDP rather than using methods developed for POMDP:s [10]. In a shortest path POMDP, we want to find a policy that takes us from an initial state to a goal.

Case Based Reasoning

In Case Based Reasoning (CBR), decisions are taken based on the observations that have been made and decisions that have been taken previously [43]. After successfully troubleshooting the system, information regarding the observations that were made and the repair action that resolved the problem is stored in a case library. The next time we troubleshoot a system, the current observations are matched with similar cases in the case library [24]. If the same repair action resolved the problem for all these cases, then this action will be taken. Information-retrieving actions can be taken to generate additional observation so that we can discriminate between cases for which different repairs solved the problem. The case library can for example initially be filled with cases from manual troubleshooting and as more cases are successfully solved the library is extended and the performance of the reasoning system improves [21]. CBR has been used successfully in several applications for troubleshooting (see e.g. [1, 21, 29]). In these applications the problem of minimizing the expected cost of repair is not considered and as with other data-driven methods these methods require large amounts of training data.

1.4 Troubleshooting Framework

For the troubleshooting task, we want to minimize the expected cost of repair. This requires that we can determine the probabilities of action outcomes and the probability distribution over possible diagnoses. This information can only be provided by the probabilistic methods for diagnoses. We will use a method for probability-based diagnosis using *non-stationary Dynamic Bayesian Networks* [56]. This method is well suited for troubleshooting since it allows us to keep track of the probability distribution over possible diagnoses when both observations and repairs can occur.

In Section 1.3.2 we mentioned that when we know the probability distribution over possible diagnoses we can solve the decision problem using look-ahead search or planning-based methods. The main advantage of the methods that use look-ahead search is that they are computationally efficient. However, when troubleshooting systems such as trucks, actions can take a long time for the user to execute. With planning-based methods this time can be used more effectively for deliberation so that a better decision can be made. We will use a planning algorithm for MDP:s to solve the decision problem. This is because we emphasize minimizing the expected cost of repair and that we want to be able to use all available computation time. Modeling the problem as an MDP works well together with a Bayesian diagnostic model.

In this thesis, we have a framework for troubleshooting, where the troubleshooter consist of two parts, a Planner and a Diagnoser. The Planner and the Diagnoser interact to produce recommendations to the user. The Diagnoser is responsible for finding the possible diagnoses and the Planner is responsible for deciding which action should be performed next. A schematic of the troubleshooting framework is shown in Figure 1.2.

The user informs the troubleshooter which actions have been performed on the system and what observations have been seen. Given this information the Troubleshooter recommends an action to perform next. The Troubleshooter uses the Diagnoser to find out what diagnoses are possible and the Planner to create a partial conditional plan of actions that minimizes the ECR given the possible diagnoses. During planning, the Planner will use the Diagnoser to estimate possible future states and the likelihoods of observations. After planning, the Troubleshooter will recommend the user to perform the first action in the plan created by the Planner. This could be an action that gains more information, replaces suspected faulty components, or in some other way affects the system.

When the Planner creates its plans, it is under time pressure. All time that is spent computing while the user is idling contributes to the total cost of repair. However, if the user is not ready to execute the recommended action because the user is busy executing a previously recommended action or doing something else, there is no loss in using this time for additional computations. We do not know precisely how long this time can be so therefore it is desirable that the Planner is an anytime planner, i.e. it is able to deliver a decision quickly if needed, but if it is given more time it can plan further and make a better

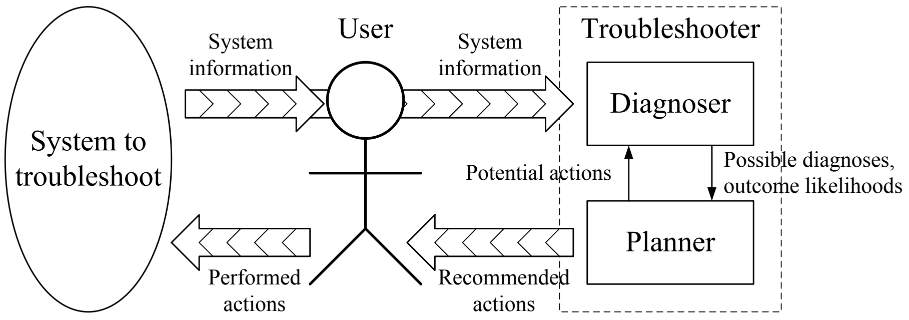


Figure 1.2: The troubleshooting framework.

decision.

Since the decision may improve over time, the best thing to do is not necessarily to abort the planning as soon as the user begins idling. The algorithm that is used for the Planner in this thesis can provide the user with an upper bound on the difference between the ECR using the current plan and the optimal ECR. The larger this bound is the greater the potential is to make a better decision. If the user sees that the bound is steadily improving the user may then decide to wait, in hope of receiving an improved recommendation that leads to a lower ECR, despite the additional computation time.

1.5 Contributions

The work described in this thesis contributes to solving the troubleshooting problem in such a way that a good trade-off between computation time and solution quality can be made. Emphasis is placed on solving the decision problem better than existing methods. A framework for troubleshooting is developed where the diagnosis problem is solved using non-stationary dynamic Bayesian networks (nsDBN) [64] and the decision problem is solved using a new algorithm called *Iterative Bounding LAO** (IBLAO*).

The main contributions are the new algorithm and new and improved heuristics for solving the decision problem by searching. The algorithm is applicable for probabilistic contingent planning in general and in this thesis it is applied to troubleshooting of subsystems of a modern truck. Pernestål [56] has developed a framework for nsDBN:s applied to troubleshooting. In this work, we show how those nsDBN:s can be converted to stationary Bayesian networks and used together with IBLAO* for troubleshooting in our application.

IBLAO* is a new efficient anytime search algorithm for creating ϵ-optimal solutions to problems formulated as Stochastic Shortest Path Problems, a subgroup of MDPs. In this thesis, we show how the troubleshooting problem can formulated as a Stochastic Shortest Path Problem. When using IBLAO* for solving the decision problem the user has access to and may monitor an upper bound of the ECR for the current plan as well as a lower bound of the optimal ECR. An advantage of this is that the user may use this information to decide whether to use the current recommendation or to allow the search algorithm to continue in hope of finding a better decision. As the algorithm is given more computation time it will converge toward an optimal solution. In comparison with competing methods, the new algorithm uses a smaller search space and for the troubleshooting problem it can make ϵ-optimal decisions faster.

The new heuristic functions that are developed for this thesis can be used by IBLAO*, and they provide strict lower and upper bounds of the optimal expected cost of repair that can be efficiently computed. The heuristics extend the utility functions in [79] and [33] by taking advantage of specific characteristics of the troubleshooting problem for heavy vehicles and similar applications. These heuristics can be used by general optimal informed search algorithms such as IBLAO* on the troubleshooting problem to reduce the search space and find solutions faster than if general heuristics are used.

The new algorithm is together with the new heuristics tested on a case study of an auxiliary hydraulic braking system of a modern truck. In the case study, state-of-the-art methods for computer-assisted troubleshooting are compared and it is shown that the current method produces decisions of higher quality. When the new planning algorithm is compared with other similar state-of-the-art planning algorithms, the plans created using IBLAO* have consistently higher quality and they are created in shorter time. The case study shows that the troubleshooting framework can be applied for troubleshooting systems from the heavy vehicles domain.

The algorithm IBLAO* has previously been published in [87]. Parts of the work on the heuristics have been published in [86, 88, 89]. Parts of the work on the troubleshooting framework have been published in [58, 85, 89]. Parts of the work on the case study have been published in [57, 89].

2

Preliminaries

This chapter is intended to introduce the reader to concepts and techniques that are central to this thesis. In particular, different types of Bayesian networks and Markov Decision Processes that can be used to model the troubleshooting problem are described.

2.1 Notation

Throughout this thesis, unless stated otherwise, the notation used is as follows.

- Stochastic variables are in capital letters, e.g. X.
- The value of a stochastic variable is in small letters, e.g. $X = x$ means that the variable X has the value x.
- Ordered sets of stochastic variables are in capital bold font, e.g $\mathbf{X} = \{X_1, \ldots, X_n\}$.
- The values of an ordered set of stochastic variable is in small bold letters, e.g. $\mathbf{X} = \mathbf{x}$ means that the variables $\mathbf{X} = \{X_1, \ldots, X_n\}$ have the values $\mathbf{x} = \{x_1, \ldots, x_n\}$.
- Variables or sets of variables are sometimes indexed with time, e.g. $X^t = x$ means that the variable X has the value x at time t and $\mathbf{X}^t = \mathbf{x}$ means that for each variable $X_i \in \mathbf{X}$, $X_i^t = x_i$. The letter t is used for discrete

event time that increases by 1 for each discrete event that occurs and τ is used for real time.

- The outcome space of a stochastic variable X is denoted Ω_X, i.e., the set of all possible values the X can have. The set of all possible outcomes of multiple variables $X_1, \ldots, X_n$ is denoted $\Omega(X_1, \ldots, X_n)$.
- The concatenation of sequences and vectors is indicated with a semi-colon, e.g. $(a, b, c); (c, d, e) = (a, b, c, c, d, e)$.

A list of all the notation and variable names used can be found in Appendix A and a list of acronyms is found in Appendix B.

2.2 Bayesian Networks

This section will give a brief overview of Bayesian networks, particularly in the context of troubleshooting. For more comprehensive work on Bayesian networks, see e.g. Jensen [39]. We will begin by describing the basic Bayesian network before we describe the concepts of causality and dynamic Bayesian networks that are needed to model the troubleshooting process.

A Bayesian network (BN) is a graphical model that represents the joint probability distribution of a set of stochastic variables $\mathbf{X}$. The definition of Bayesian networks used in this thesis follows the definition given in [40].

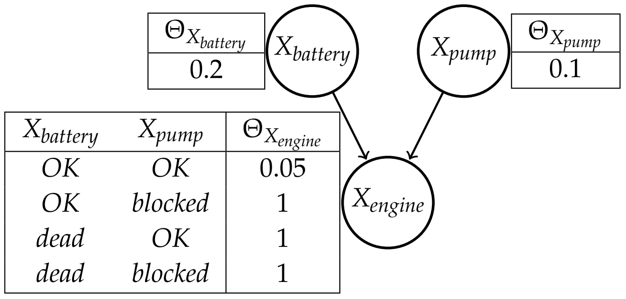
Definition 2.1 (Bayesian Network)**.** A Bayesian network is a triple $B = \langle \mathbf{X}, \mathbf{E}, \Theta \rangle$ where $\mathbf{X}$ is a set of stochastic variables and $\mathbf{E}$ is a set of directed edges between the stochastic variables s.t. $(\mathbf{X}, \mathbf{E})$ is a directed acyclic graph. The set Θ contains parameters that define the conditional probabilities $P(X|pa(X))$ where $pa(X)$ are the parents of X in the graph.

The joint probability distribution of all the stochastic variables $\mathbf{X}$ in the Bayesian network is the product of each stochastic variable $X \in \mathbf{X}$ conditioned on its parents:

$$P(\mathbf{X}) = \prod_{X \in \mathbf{X}} P(X|pa(X)).$$

Let $\Theta_X \subseteq \Theta$ be the parameters that define all the conditional probabilities $P(X|pa(X))$ of a specific variable X. This set Θ_X is called the *conditional probability distribution* (CPD) of X. When the variables are discrete, the CPD is called the *conditional probability table* (CPT).

Bayesian networks can be used to answer queries about the probability distribution of a variable given the value of others.



$\Theta_{X_{battery}}$
0.2

$\Theta_{X_{pump}}$
0.1

$X_{battery}$	X_{pump}	$\Theta_{X_{engine}}$
OK	*OK*	0.05
OK	*blocked*	1
dead	*OK*	1
dead	*blocked*	1

Figure 2.1: The Bayesian network in Example 2.1. The parameters $\Theta_{X_{battery}}$, $\Theta_{X_{pump}}$, and $\Theta_{X_{engine}}$ describe the conditional probabilities of having $X_{battery} = dead$, $X_{pump} = blocked$, and $X_{engine} = notstarting$ respectively.

Example 2.1 (Simple Car Model)**.** Consider a car where the engine will not start if the battery is dead or the fuel pump is blocked. When nothing else is known, the probability of a dead battery is 0.2 and the probability of a blocked fuel pump is 0.1. Also, even if both battery and the fuel pump are OK the engine may still be unable to start with a probability of 0.05.

From this description, a Bayesian network $B_{ex2.1}$ can be created that has the variables $\mathbf{X} = (X_{engine}, X_{battery}, X_{pump})$ and the two edges $(X_{battery}, X_{engine})$ and (X_{pump}, X_{engine}). The graph and conditional probability tables for $B_{ex2.1}$ are shown in Figure 2.1. The joint probability distribution represented by $B_{ex2.1}$ is:

X_{engine}	$X_{battery}$	X_{pump}	$P(X_{engine}, X_{battery}, X_{pump})$
starting	*OK*	*OK*	0.684
starting	*OK*	*blocked*	0
starting	*dead*	*OK*	0
starting	*dead*	*blocked*	0
not starting	*OK*	*OK*	0.036
not starting	*OK*	*blocked*	0.08
not starting	*dead*	*OK*	0.18
not starting	*dead*	*blocked*	0.02

When answering a query $P(\mathbf{X}|\mathbf{Y})$, the structure of the network can be used to determine which variables in $\mathbf{X}$ that are conditionally independent given $\mathbf{Y}$. These variables are said to be *d*-separated from each other [53]. We will use the same definition of *d*-separation as in Jensen and Nielsen [40].

Definition 2.2 (*d*-separation)**.** A variable $X_i \in \mathbf{X}$ of a BN $\langle \mathbf{X}, \mathbf{E}, \Theta \rangle$ is *d-separated* from another variable $X_j \in \mathbf{X}$ given $\mathbf{Y} \subseteq \mathbf{X}$ if all undirected paths $\mathbf{P} \subseteq \mathbf{E}$ from

X_i to X_j are such that $\mathbf{P}$ contains a subset of connected edges such that:

- the edges are serial, i.e. all edges are directed the same way, and at least one intermediate variable belongs to $\mathbf{Y}$,
- the edges are diverging, i.e. the edges diverge from a variable Z in the path, and $Z \in \mathbf{Y}$, or
- the edges are converging, i.e. the edges meet at a variable Z in the path, and $Z \notin \mathbf{Y}$.

The property of *d*-separation is symmetric, i.e. if X_i is *d*-separated from X_j given $\mathbf{Y}$, then X_j is *d*-separated from X_i given $\mathbf{Y}$.

The property of *d*-separation is useful because it enables us to ignore the part of the network containing X_j when answering the query $P(X_i|\mathbf{Y})$. Consider Example 2.1. If we have no evidence for any variable, then $X_{battery}$ is *d*-separated from X_{pump} given $\mathbf{Y} = \emptyset$ since the path between them is converging at X_{engine} and $X_{engine} \notin \mathbf{Y}$. This means that we can for example compute $P(x_{battery}|x_{pump})$ simply by computing $P(x_{battery})$. However, if we have evidence for X_{engine}, then $X_{battery}$ and X_{pump} are not *d*-separated given $\mathbf{Y} = \{X_{engine}\}$. Then if we for example want to compute $P(x_{battery}|x_{engine})$, we must consider X_{pump}:

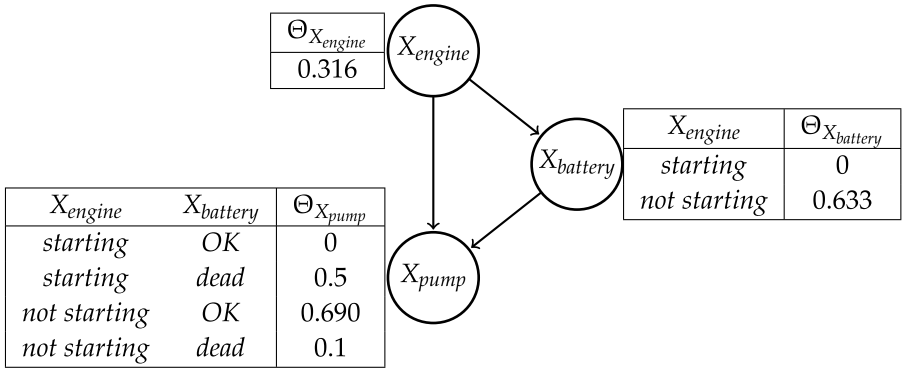
$$P(x_{battery}|x_{engine}) = \frac{\sum\limits_{x_{pump} \in \Omega(X_{pump})} P(x_{engine}|x_{battery}, x_{pump})P(x_{battery})P(x_{pump})}{\sum\limits_{x'_{battery}, x'_{pump} \in \Omega(X_{battery}, X_{pump})} P(x_{engine}|x'_{battery}, x'_{pump})P(x'_{battery})P(x'_{pump})}.$$

2.2.1 Causal Bayesian Networks

If there is an edge between two variables X_i and X_j and the variables are such that the value of X_i physically causes X_j to have a certain value, this edge is said to be causal [54]. E.g., a dead battery or a blocked pump causes the engine to not start. If all edges in a BN are causal, we say that the BN is a *causal Bayesian network*.

It is often easier to model a physical system with a causal BN than with a BN that does not follow the causal relationships. The BN in Example 2.1 is causal since having a dead battery and a blocked pump causes the engine not to start. However, the same joint probability distribution, $P(X_{engine}, X_{battery}, X_{pump})$, can be modeled with other BN:s that do not follow the causal relationships.

Example 2.2 (Non-causal Equivialent). Consider a BN $B_{ex2.2}$ with same set of stochastic variables as $B_{ex2.1}$ from the previous example, but with the edges $[X_{engine}, X_{pump}]$, $[X_{battery}, X_{pump}]$ and $[X_{engine}, X_{battery}]$. The graph and CPT:s for $B_{ex2.1}$ are shown in Figure 2.2.



$\Theta_{X_{engine}}$
0.316

X_{engine}	$\Theta_{X_{battery}}$
starting	0
not starting	0.633

X_{engine}	$X_{battery}$	$\Theta_{X_{pump}}$
starting	*OK*	0
starting	*dead*	0.5
not starting	*OK*	0.690
not starting	*dead*	0.1

Figure 2.2: The Bayesian network in Example 2.2. The parameters $\Theta_{X_{battery}}$, $\Theta_{X_{pump}}$, and $\Theta_{X_{engine}}$ describe the conditional probabilities of having $X_{battery} =$ *dead*, $X_{pump} =$ *blocked*, and $X_{engine} =$ *not starting* respectively.

The joint probability distribution represented by $B_{ex2.2}$ is exactly the same as the one represented by $B_{ex2.1}$. However, the CPT:s of $B_{ex2.2}$ are less intuitive. For example, the original model specified separate probabilities of the engine failing to start depending on whether the battery was dead and/or the pump was blocked. In this model, these probabilities are baked into a single unconditional probability of 3.16. That is, the pump and/or the battery are faulty with the probability 0.28 ($0.2 + 0.1 - 0.2 \cdot 0.1$) and then the engine will fail to start with probability 1.0. If neither is faulty, the engine will fail to start with probability 0.05, i.e. $0.316 = 0.28 \cdot 1.0 + 0.05 \cdot (1 - 0.28)$.

Interventions

An *intervention* is when a variable is forced to take on a certain value rather than just being observed. If the BN is causal, we may handle interventions in a formal way [54]. The variable that is intervened with becomes independent of the values of its parents, e.g. if we break the engine, its status is no longer dependent on the pump and battery since it will not start anyway. When an intervention occurs, a new BN is created by disconnecting the intervened variable from its parents and setting it to the forced value. In the troubleshooting scenario, interventions occur when components are repaired. Since repairs are a natural part of the troubleshooting process we need to handle interventions and thus use a causal Bayesian network.

Example 2.3. Consider a BN with the variables X_{rain} that represents whether it has rained or not and X_{grass} that represents whether the grass is wet or not.

We know that the probability for rain is 0.1 and that if it has rained the grass will be wet and otherwise it will be dry. If we observe that it the grass is wet we can draw the conclusion that it has rained with probability 1.0. However, if take a hose and wet the grass we perform an intervention on the grass. Then if we observe that the grass is wet, the probability that it has rained is still 0.1:

$$P(X_{rain} = \textit{has rained} | X_{grass} = \textit{wet}, X_{grass} := \textit{wet}).$$

where $X_{grass} := \textit{wet}$ means that the variable X_{grass} is forced to take on the value *wet* by an external intervention[1].

2.2.2 Dynamic Bayesian Networks

Because we perform actions on the system, troubleshooting is a stochastic process that changes over time. Such processes can be modeled as dynamic Bayesian networks [19].

Definition 2.3 (Dynamic Bayesian Network). A *dynamic Bayesian network* (DBN) is a Bayesian network where the set of stochastic variables can be partitioned into sets $\mathbf{X}^0, \mathbf{X}^1, \ldots$ where $\mathbf{X}^t$ describes the modeled process at the discrete time point t. $\square$

If for each variable $X^t \in \mathbf{X}^t$ it is the case that $pa(X^t) \subset \bigcup_{k=0}^{n} \mathbf{X}^{t-k}$, the DBN is said to be an n:th order DBN. In other words, all the variables in $\mathbf{X}^t$ are only dependent of the values of the variables up to n time steps earlier. The stochastic variables $\mathbf{X}^t$ and the edges between them form a Bayesian network B^t called the *time slice* t. The network B^t is a subgraph of the DBN.

If all time slices $t > 0$ are identical, the DBN is said to be *stationary*. A stationary first order DBN B can be fully represented by an *initial BN* B^0 and a *transition BN* $B^{\rightarrow}$ representing all other BN:s $B^1, B^2, \ldots$ in the DBN. The variables in $B^{\rightarrow}$ are $\bigcup_{X^t \in \mathbf{X}^t}(\{X^t\} \cup pa(X^t))$ for some arbitrary $t > 0$ and the edges are all edges between variables in $\mathbf{X}^t$ and all edges from variables in $pa(X^t)$ to $X^t \in \mathbf{X}^t$. Often in the literature DBN:s are assumed to be first order stationary DBN:s (see e.g. [48, 66]).

A DBN where the probabilistic dependencies change between time slices is said to be *non-stationary* [64]. Non-stationary dynamic Bayesian networks (nsDBN:s) are more general than stationary DBN:s and can handle changes to the network that arise with interventions such as repair actions in troubleshooting.

[1]Often, such as in the work by Pearl [54], the notation $Do(X^{t+1} = x)$ is used to describe intervention events, but it is the author's opinion that $X^{t+1} := x$ is more compact and appropriate since the concept of intervention on a variable is similar to the assignment of a variable in programming.

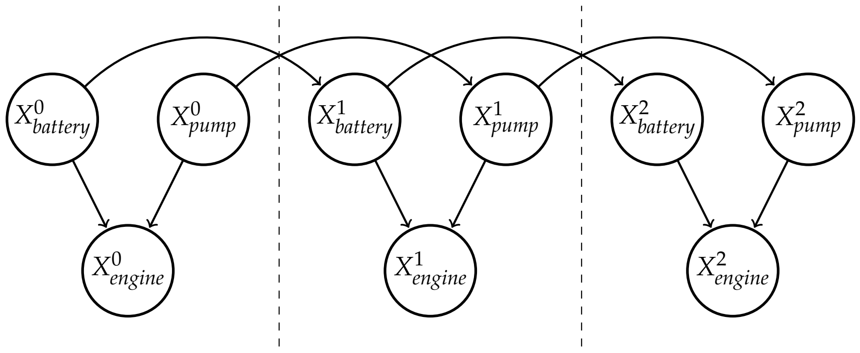


Figure 2.3: The first three time slices of $B_{ex2.4}$ in Example 2.4.

Example 2.4 (Dynamic Bayesian Network)**.** The BN $B_{ex2.1}$ can be made into a DBN $B_{ex2.4}$ where the states of the battery and the pump do not change over time by letting the variables $X^t_{battery}$ and X^t_{pump} depend on $X^{t-1}_{battery}$ and X^{t-1}_{pump} so that $P(x^t_{battery}|x^{t-1}_{battery}) = P(x^t_{pump}|x^{t-1}_{pump}) = 1$. The first three time slices of $B_{ex2.4}$ are shown in Figure 2.3.

If the engine is observed to not start at time 0 and we then *observe* that the pump is OK at time 1 we can infer that the battery must be dead at time 2. If we instead *remove* any blockage in the fuel pump at time 1 we have the knowledge that the pump is OK, but the probability that the battery is dead at time 2 is now 0.633, not 1.0, because the pump could still have been blocked at time 0. The action of removing the blockage is an intervention on the variable X^1_{pump} that removes the dependency between X^0_{pump} and X^1_{pump}. By allowing these types of interventions $B_{ex2.4}$ becomes an nsDBN.

For Example 2.4, a DBN is not really needed since the variables cannot change values over time unless we allow interventions or we want to model that components may break down between time slices.

2.2.3 Non-Stationary Dynamic Bayesian Networks for Troubleshooting

In Pernestål [56] a framework for representing non-stationary dynamic Bayesian networks in the context of troubleshooting is developed. In this framework interventions relevant for troubleshooting are treated. The *nsDBN for troubleshooting* is causal and describes the probabilistic dependencies between components and observations in a physical system. The same compact representation of the structure with an initial BN and a transition BN that is applicable for stationary DBN:s is not possible for general non-stationary DBN:s. However, the nsDBN for troubleshooting can be represented by an initial BN B^0_{ns} and a set of rules describing how to generate the consecutive time slices.

Events

The nsDBN for troubleshooting is event-driven, i.e. a new time slice is generated whenever a new event has occurred. This differs from other DBN:s where the amount of time that elapses between each time slice is static. An event can either be an *observation*, a *repair*, or an *operation of the system*. If the system is a vehicle, the operation of the system is to start the engine and drive for a certain duration of time. After each event, a *transition* occurs and a new time slice is generated. We use the notation $X^{t+1} = x$ to describe the event that the variable X is observed to have the value x at time $t+1$ and $X^{t+1} := x$ to describe a repair event that causes X to have the value x at time $t+1$. For the event that the system is operated for a duration of τ time units between the time slices t and $t+1$, we use the notation $\omega^{t+1}(\tau)$. Note that the duration τ is a different time measure than the one used for the time slices which is an index.

Persistent and Non-Persistent Variables

The variables in the nsDBN for troubleshooting are separated into two classes: *persistent* and *non-persistent*. The value of a persistent variable in one time slice is dependent on its value in the previous time slice and may only change value due to an intervention such as a repair or the operation of the system. A component's state is typically modeled as a persistent variable, e.g., if it is broken at one time point it will remain so at the next unless it is repaired. A non-persistent variable is not directly dependent on its previous value and cannot be the parent of a persistent variable. Observations are typically modeled with non-persistent variables, e.g. the outcome of an observation is dependent on the status of another component.

Instant and Non-Instant Edges

The edges in an nsDBN for troubleshooting are also separated into two classes: *instant* and *non-instant*. An instant edge always connects a parent variable to its child within the same time slice. This means that a change in value in the parent has an instantaneous impact on the child. An instant edge typically occurs between a variable representing the reading from a sensor and a variable representing the measured quantity, e.g. a change in the fuel level will have an immediate effect on the reading from the fuel level sensor.

A non-instant edge connects a child variable in one time slice to a persistent parent variable in the first time slice after the most recent operation of the system. If no such event has occurred it connects to a persistent parent variable in the first time slice of the network. Non-instant edges model dependencies that are only active during operation. For example, the dependency between a variable representing the presence of leaked out oil and a variable representing a component that may leak oil is modeled with a non-instant edge if new oil can only leak out when the system is pressurized during operation.

Transitions

There are three types of transitions that may occur: *nominal transition*, *transition after operation*, and *transition after repair*. When an observation event has occurred the nsDBN makes a nominal transition. Then all variables $X^t \in \mathbf{X}^t$ from time slice t are copied into a new time slice $t+1$ and relabeled X^{t+1}. For each instant edge (X_i^t, X_j^t) where X_j^t is non-persistent, an instant edge (X_i^{t+1}, X_j^{t+1}) is added. Let t_ω be the time of the most recent operation event or 0 if no such event has occurred. For each non-instant edge $(X_i^{t_\omega}, X_j^t)$ where X_j^t is non-persistent, an edge $(X_i^{t_\omega}, X_j^{t+1})$ is added. For each persistent variable X^{t+1}, an edge (X^t, X^{t+1}) is added. In Pernestål [56] the nominal transition is referred to as the transition after an empty event.

Transitions After Operation

When the system is operated between times t and $t+1$, a transition after operation occurs. During such a transition, persistent variables may change values. All variables $\mathbf{X}^0$ and edges (X_i^0, X_j^0) from time slice 0 are copied into the new time slice $t+1$ and labeled $\mathbf{X}^{t+1}$ and (X_i^{t+1}, X_j^{t+1}) respectively. Also, for each persistent variable X^{t+1}, an edge (X^t, X^{t+1}) is added. The conditional probability distributions of the persistent variables are updated to model the effect of operating the system. Such a distribution can for example model the probability that a component breaks down during operation. Then this distribution will be dependent on the components' state before the operation event occurs. The distribution can also be dependent on the duration of the operation event.

Transition After Repair

When a component variable X is repaired, a transition after repair occurs. This transition differs from the nominal transition in that the repair is an intervention on the variable X and therefore X^{t+1} will have all its incoming edges re-

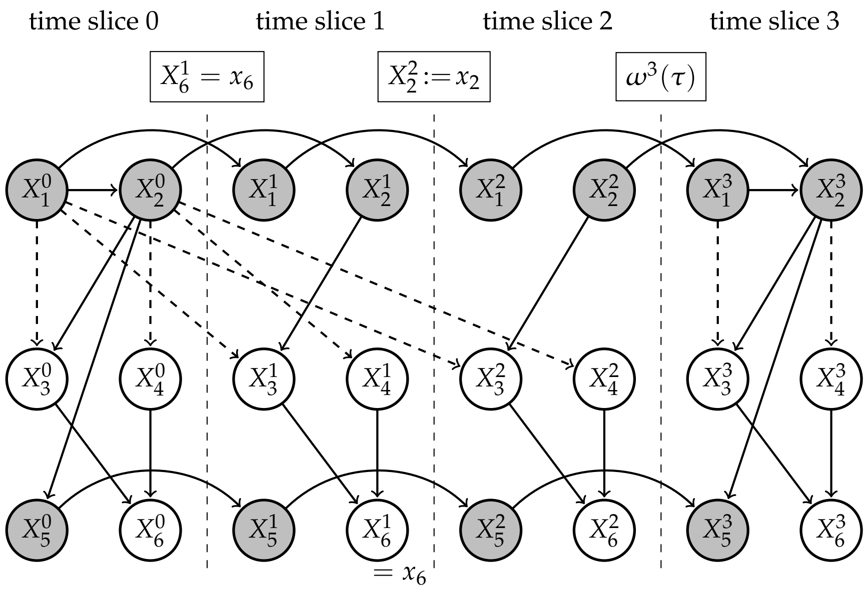


Figure 2.4: Transitions in an nsDBN.

moved. The new conditional probability distribution of X^{t+1} will depend on the specific repair event. For example, it will depend on the success rate of the repair.

Example 2.5. Figure 2.4 shows an example of an nsDBN from time slice 0 to 3. Persistent variables are shown as shaded circles, non-persistent variables are shown as unfilled circles, instant edges are shown as filled arrows, and non-instant edges as dashed arrows. The first transition, after the observation $X_6^1 = x_6$, is nominal. The second transition is after the intervention $X_2^2 := x_2$ and the third is after operation. After the operation, the time slice looks the same as in the first time slice. If, instead of $\omega^3(\tau)$, we would have observed the variable X_6 again, this variable would have a value that is dependent on X_2^0 before the intervention.

Parameters

The parameters required for the nsDBN for troubleshooting describe the dependencies within the first time slice, Θ_X^0, and the dependencies between persistent variables and their copies in the next time slice after a transition after operation, Θ_X^ω. For subsequent time slices these parameters are reused, e.g. in time slice 2 of Example 2.5, $P(X_3^2|X_1^0, X_2^2) = \Theta^0_{X_3}(X_1, X_2)$.

Definition 2.4 (nsDBN)**.** An *nsDBN* is a tuple $B_{ns} = \langle \mathbf{X}_p, \mathbf{X}_{np}, \mathbf{E}_i, \mathbf{E}_{ni}, \Theta^0, \Theta^\omega \rangle$ where $\mathbf{X}_p$ are the persistent variables, $\mathbf{X}_{np}$ are the non-persistent variables, and $\mathbf{E}_i$ and $\mathbf{E}_{ni}$ are the instant edges and non-instant edges in the first time slice respectively. The parameters Θ^0 specify the conditional probability distributions for all variables in the first time slice so that $\langle \mathbf{X}_p \cup \mathbf{X}_{np}, \mathbf{E}_i \cup \mathbf{E}_{ni}, \Theta^0 \rangle$ is an ordinary BN. The parameters Θ^ω specify the conditional probabilities for the transitions after operation. □

Let B_{ns} be an nsDBN and let $\mathbf{e}^{1:t}$ be a sequence of events that has occurred, then $B_{ns}(\mathbf{e}^{1:t})$ is the Bayesian network that is obtained by adding new time slices to the nsDBN using the corresponding transition rule for each event in $\mathbf{e}^{1:t}$.

2.2.4 Inference in Bayesian Networks

The process of answering a query $P(\mathbf{X}|\mathbf{Y})$ is called *inference*. The probability distribution over $\mathbf{X}$ is inferred from the BN model given the evidence $\mathbf{Y}$. The inference can be exact or approximate. For general discrete Bayesian networks, the time and space complexity of exact inference is exponential in the size of the network, i.e., the number of entries in the conditional probability tables [66]. In this section, we will describe the most basic methods for making inference in BN:s.

Variable Elimination Algorithm

Variable Elimination [66] is an algorithm for exact inference in BN:s. Other algorithms in the same family include Bucket Elimination [20] and Symbolic Probabilistic Inference [73].

Let $\langle \mathbf{X}, \mathbf{E}, \Theta \rangle$ be a BN where the variables $\mathbf{X} = (X_0, \ldots, X_n)$ are ordered so that $X_i \notin pa(X_j)$ if $j < i$ and let $\mathbf{Y} \subseteq \mathbf{X}$ be the set of variables we want to obtain a joint probability distribution over. Further, let $\mathbf{Y}_i^+ = \mathbf{Y} \cap \bigcup_{k=i}^{n} X_k$ be the set of variables in $\mathbf{Y}$ that have the position i or greater in $\mathbf{X}$, and let $\mathbf{X}_i^- = \bigcup_{k=0}^{i-1} X_k$ be the set of variables in $\mathbf{X}$ that have the position $i - 1$ or less in $\mathbf{X}$. Then the joint probability distribution over $\mathbf{Y}$, $P(\mathbf{y}) = P(\mathbf{y}_0^+|\mathbf{x}_0^-)$ where

$$P(\mathbf{y}_i^+|\mathbf{x}_i^-) = \begin{cases} P(y_i|\mathbf{x}_i^-) & \text{if } i = n \text{ and } X_i \in \mathbf{Y}, \\ 1 & \text{if } i = n \text{ and } X_i \notin \mathbf{Y}, \\ P(y_i|\mathbf{x}_i^-)P(\mathbf{y}_{i+1}^+|\mathbf{x}_i^- \cup x_i) & \text{if } i < n \text{ and } X_i \in \mathbf{Y}, \\ \sum_{x_i \in X_i} P(x_i|\mathbf{x}_i^-)P(\mathbf{y}_{i+1}^+|\mathbf{x}_i^- \cup y_i) & \text{if } i < n \text{ and } X_i \notin \mathbf{Y}. \end{cases} \tag{2.1}$$

The Variable Elimination algorithm solves (2.1) using dynamic programming so that the results of repeated calculations are saved for later use.

Message-Passing

If the BN is a tree it is possible to do inference in time linear in the size of the network by using the method of message passing [51]. The size of the network again refers to the number of entries in the conditional probability tables. A general BN can be converted into a tree, but in the worst case, this operation may cause the network to grow exponentially [52].

Approximate Methods

If the BN is large it may be necessary to do approximate inference. Many of the methods for approximate inference depend on some randomization process such as sampling from the prior distribution and give each sample some weight based on their importance to explaining the evidence. These kinds of methods are often used for DBN:s in real-time applications such as robotics (see e.g. Thrun et al. [80]).

2.3 Markov Decision Processes

The troubleshooting problem is a decision process where actions may be chosen freely by the decision maker to achieve the goal of repairing the system but the actions may have stochastic outcomes. Markov Decision Processes (MDP:s) provide a powerful mathematical tool to model this. This section gives a brief overview of some types of MDP:s that are relevant for this thesis. For more information on MDP:s, see e.g. [60].

2.3.1 The Basic MDP

In an MDP, a state is a situation in which a decision of what action to perform must be made. Depending on the action and the outcome of the action, a different state may be reached. Depending on the decision and the state where the decision is made an immediate positive or negative reward is given. The goal is to find a decision rule that maximizes the expected total reward over a sequence of actions.

Definition 2.5 (Markov Decision Process)**.** A *Markov Decision Process* is a tuple

$$\langle \mathcal{S}, \mathcal{A}, p, r \rangle$$

where $\mathcal{S}$ is a state space, $\mathcal{A}$ is a set of possible actions, $p : \mathcal{S}^2 \times \mathcal{A} \mapsto [0, 1]$ is a transition probability function where $\forall\, s \in \mathcal{S}, a \in \mathcal{A}\ \int_{s' \in \mathcal{S}} p(s', s, a) ds' = 1$, and $r : \mathcal{A} \times \mathcal{S} \mapsto \mathbb{R}$ is a reward function. □

In the general case, the state space and the set of possible actions may be continuous, but for the application of MDP:s used in this thesis, we will only consider MDP:s where the set of possible actions is discrete and finite.

The value $p(s', s, a)$ specifies the probability that the state s' is reached given that the action a is performed in state s. Each state that can be reached with a non-zero probability corresponds to one possible outcome of the action. We will assume that each action will only have a finite number of outcomes in any state. Those states that have non-zero probability of being reached are specified by the the successor function.

Definition 2.6 (Successor function)**.** The *successor function* is a function $succ : \mathcal{A} \times \mathcal{S} \mapsto 2^{\mathcal{S}}$ such that $succ(a, s) = \{s' \in \mathcal{S} : p(s', s, a) > 0\}$. □

A graphical representation of a small discrete MDP with two states and two actions is shown in Figure 2.5. The states are shown as nodes and state transitions as edges. State transitions that correspond to the same action being performed in the same state but with different possible outcomes, are shown joined with an arc.

Policies

A decision rule for an MDP is called a policy. A policy is a function $\pi : \mathcal{S} \mapsto \mathcal{A}$ where $\pi(s)$ specifies which action that should be performed in state s. This means that the policy indirectly specifies action plans that are dependent on actual action outcomes and can result in an infinite number of actions being performed. The quality of such a policy can be measured using the *total expected discounted reward* criterion. The total expected discounted reward of a policy π is given by a function $V_\pi^\gamma : \mathcal{S} \mapsto \mathbb{R}$ where $\gamma \in [0, 1]$ is a discount factor and

$$V_\pi^\gamma(s) = r(\pi(s), s) + \gamma \sum_{s' \in succ(\pi(s), s)} p(s', s, \pi(s)) V_\pi^\gamma(s'). \tag{2.2}$$

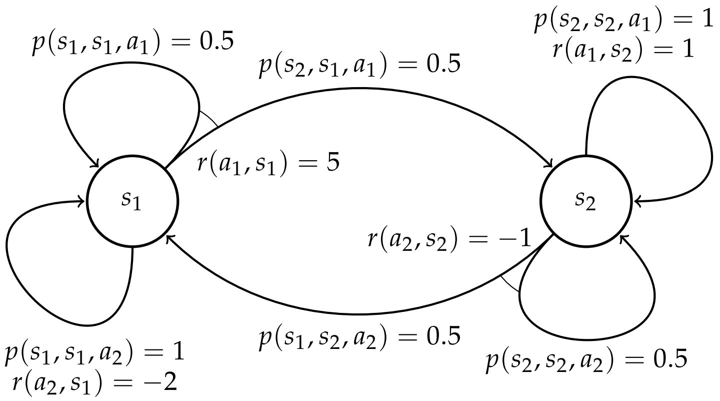


Figure 2.5: An example of a small discrete MDP $\langle \{s_1, s_2\}, \{a_1, a_2\}, p, r \rangle$.

The discount factor γ enables us to value future rewards less than immediate rewards. When the discount factor is 1.0 then (2.2) is the expectation of the total accumulated reward gained from using the decision rule over an infinitely long period of time. This would mean that the reward can be infinite, but if $\gamma < 1$ and all rewards are finite, then $V^{\gamma}_{\pi}(s) < \infty$ for all policies π and all states s.

An *optimal* policy π^* has the maximal expected discounted reward $V^{\gamma}_{\pi^*}$ in all states s:

$$\pi^*(s) = \arg\max_{a \in \mathcal{A}} \Big(r(a,s) + \gamma \sum_{s' \in succ(a,s)} p(s', s, a) V^{\gamma}_{\pi^*}(s') \Big). \tag{2.3}$$

2.3.2 Partial Observability

In troubleshooting, the state of the system can for example be its true diagnosis, i.e., the status of all components. The true diagnosis is however not known, but we can get feed-back in the form of observations that can give us information of which diagnoses are likely to be true. Such a state is said to be partially observable. An MDP with partially observable states is a *Partially Observable MDP* (POMDP) [12].

Definition 2.7 (Partially Observable MDP). A *Partially Observable MDP* is a tuple

$$\langle \mathcal{S}, \mathcal{A}, \mathcal{O}, r, p, \omega \rangle$$

where $\mathcal{S}$ and $\mathcal{A}$ are finite, $\langle \mathcal{S}, \mathcal{A}, r, p \rangle$ is an MDP, $\mathcal{O}$ is a set of possible observations and $\omega : \mathcal{O} \times \mathcal{S} \times \mathcal{A} \mapsto [0, 1]$ is a function where $\omega(o, s, a)$ is the probability of making the observation $o \in \mathcal{O}$ given that action a is performed in state s. □

Since the true state is not known, our knowledge of this state is represented as a probability distribution over the state space. In the POMDP framework, this distribution is called the *belief state b*.

Definition 2.8 (Belief State)**.** A *belief state* is a function $b : \mathcal{S} \mapsto [0,1]$ where $b(s)$ denotes the probability that the state s is the true state. The set $\mathcal{B}$ is the space of all possible belief states. □

A POMDP policy is then a function from belief states to actions, i.e. a function $\pi : \mathcal{B} \mapsto \mathcal{A}$. When an action a is performed in a belief state b and an observation o is made, the next belief state b' is computed for each state s, as [12]:

$$b'(s) = \Big(\omega(o,s,a) \sum_{s' \in succ(a,s)} p(s', s, a) b(s')\Big) \Big/ \eta(o,b,a) \tag{2.4}$$

where η is a function that gives the probability of reaching b' from b:

$$\eta(o,b,a) = \sum_{s \in \mathcal{S}} \Big(\omega(o,s,a) \sum_{s' \in succ(a,s)} p(s', s, a) b(s')\Big)$$

This function normalizes b' ensuring that $\sum_{s \in \mathcal{S}} b'(s) = 1$.

Let $\tau : \mathcal{O} \times \mathcal{B} \times \mathcal{A} \mapsto \mathcal{B}$ be a function that computes the next belief state using (2.4). Then the total expected discounted reward of a POMDP policy π is a function $V^{\gamma}_{\pi} : \mathcal{B} \mapsto \mathbb{R}$ where $\gamma \in [0,1]$ is a discount factor and

$$V^{\gamma}_{\pi}(b) = \sum_{s \in \mathcal{S}} b(s) r(\pi(b), s) + \gamma \sum_{o \in \mathcal{O}} \eta(o,b,a) V^{\gamma}_{\pi}(\tau(o,b,a)). \tag{2.5}$$

An *optimal* POMDP policy π^* has the maximal expected discounted reward $V^{\gamma}_{\pi^*}$ in every belief state b:

$$\pi^*(b) = \operatorname*{arg\,max}_{a \in \mathcal{A}} \Big(\sum_{s \in \mathcal{S}} b(s) r(\pi(b), s) + \gamma \sum_{o \in \mathcal{O}} \eta(o,b,a) V^{\gamma}_{\pi}(\tau(o,b,a))\Big). \tag{2.6}$$

Belief-MDP:s

It is possible to convert any POMDP into an ordinary MDP [12]. This allows us to find policies for the POMDP using algorithms designed for MDP:s which is something we will do in this thesis. If the current belief state is known and an action is performed the resulting belief state leads to a unique next belief state. In other words, a belief state can be seen as a fully observable state in an MDP. This is called a *belief-MDP*.

Definition 2.9 (Belief-MDP)**.** Let $\langle \mathcal{S}, \mathcal{A}, \mathcal{O}, r, p, \omega \rangle$ be a POMDP and $\mathcal{B}$ be the belief state space over $\mathcal{S}$. The corresponding *belief-MDP* is an MDP

$\langle \mathcal{S}', \mathcal{A}', r', p' \rangle$ where the state space $\mathcal{S}' = \mathcal{B}$ is the belief state space of the POMDP, the set of possible actions $\mathcal{A}' = \mathcal{A}$ remains the same, $r'(a,b) = \sum_{s \in \mathcal{S}} b(s) r(a,s)$ is the expected reward of performing a in b, and $p'(b', b, a) = \eta(o, b, a)$ is the probability of reaching the belief state b' by performing a in the belief state b where o is an observation such that $\tau(o, b, a) = b'$. □

2.3.3 Stochastic Shortest Path Problems

A stochastic shortest path problem (SSPP) is a problem that can be modeled with an MDP where we want to reach one of a set of goal states from a given initial state [6]. Performing an action is associated with a cost and the actions may have stochastic outcomes. An SSPP can be used to encode many problems where a plan of actions leading to a goal state is sought. One such problem is the problem of computer-assisted troubleshooting. SSPP:s correspond to MDP:s where all rewards are non-positive, and some states are *absorbing*, i.e. the reward for performing any action in an absorbing state is zero and we will end up in the same state with probability 1.0.

The absorbing states are the goal states that we want to reach and the non-positive reward function encodes the cost of performing actions in each state. For simplicity, we will model the cost of performing actions directly with a cost function.

Definition 2.10 (Cost Function)**.** The *cost function* is a function $c : \mathcal{S} \times \mathcal{A} \mapsto \mathbb{R}^+$ such that $c(a,s)$ is the cost of performing the action a in the state s. □

Definition 2.11 (Stochastic Shortest Path Problem)**.** A *Stochastic Shortest Path Problem* is a tuple

$$\langle \mathcal{S}, \mathcal{A}, p, c, s_0, \mathcal{S}_g \rangle$$

where $\langle \mathcal{S}, \mathcal{A}, p, -c \rangle$ is an MDP, s_0 is the initial state, and $\mathcal{S}_g$ is the set of absorbing goal states. All states $s \in \mathcal{S}_g$ are such that, for all actions $a \in \mathcal{A}$, $p(s,s,a) = 1$ and $c(a,s) = 0$. All other states $s \notin \mathcal{S}_g$ are such that, for all actions $a \in A$, $c(a,s) > 0$. □

A policy for an SSPP is a policy for the corresponding MDP. Therefore and because the cost function is the negative reward function of the corresponding MDP, the expected cost of a policy π of an SSPP is a function defined as $V_\pi = -V_\pi^\gamma$ where $\gamma = 1$. An optimal policy π^* has minimal expected cost in all states s:

$$V_{\pi^*}(s) = \min_{a \in \mathcal{A}} r(a,s) + \sum_{s' \in succ(a,s)} p(s', s, a) V_{\pi^*}(s'). \tag{2.7}$$

Since the SSPP has absorbing goal states, it may be possible to find a policy that can reach a goal state from the initial state with a finite expected cost since in the absorbing states all infinite sequences of actions will have an expected cost that is zero. Such a policy exists if all action costs are finite and if by following the policy from the initial state, a goal state will eventually be reached.

2.3.4 Finding the Optimal Policy for an MDP

In this section we will go through some methods for finding optimal or suboptimal policies for the different types of MDP:s described in Sections 2.3.1–2.3.3.

Value Iteration

Value Iteration [3] is a standard method for finding near optimal policies for ordinary MDP:s with discrete state spaces. When the discount factor $\gamma < 1$, Value Iteration can find a policy π where $V^{\gamma}_{\pi^*}(s) - V^{\gamma}_{\pi}(s) < \epsilon$ in all states s for an arbitrary small $\varepsilon > 0$. The Value Iteration algorithm is shown below as Algorithm 1.

A function $f : \mathcal{S} \mapsto \mathbb{R}$ called the *value function* approximates the expected reward of the policy π that is returned from the algorithm. The value function holds a value for each state and each value is initialized with an arbitrary initial guess as given by the function $h : \mathcal{S} \mapsto \mathbb{R}$. In each iteration through the lines 5–10, the values in f will converge further toward the optimal expected reward function $V^{\gamma}_{\pi^*}$. The operation in line 7 of updating the value of f for a state s is called a backup of state s. In line 12 a policy π is created that is greedy in the value function. Clearly, if $f(s) = V^{\gamma}_{\pi^*}(s)$ for all $s \in \mathcal{S}$, then line 12 is the same as (2.3) and π is optimal. When the largest change Δ in the value function for any state after an iteration is smaller than $\varepsilon(1-\gamma)/2\gamma$, then it can be shown that $V^{\gamma}_{\pi^*}(s) - V^{\gamma}_{\pi}(s) < \varepsilon$ for all states s [60].

The closer the initial guess is to real optimal expected cost, the faster Value Iteration will converge. The states are backed up an equal number of times. Depending on the order in which the states are backed up, convergence toward an optimal policy can be faster or slower. It is possible to construct algorithms that are similar to Value Iteration and that back up certain states in the value function more often than other states. To guarantee that the value function converges toward the optimal expected reward, it is sufficient that the probability that each state will be backed up infinitely often is 1.0 during an infinite sequence of backups. This means that all states must have a non-zero probability of being backed up.

Algorithm 1 Value Iteration

```
1: procedure ValueIteration($MDP,\gamma,\varepsilon,h$)
2:     for each $s \in \mathcal{S}$ do $f(s) \leftarrow h(s)$
3:     $\Delta \leftarrow \infty$
4:     while $\Delta \geq \varepsilon(1-\gamma)/2\gamma$ do
5:         $\Delta \leftarrow 0$
6:         for each $s \in \mathcal{S}$ do
7:             $p \leftarrow \max_{a\in\mathcal{A}} r(a,s) + \sum_{s'\in succ(a,s)} p(s',a,s)f(s)$
8:             $\Delta \leftarrow \max(\Delta, |f(s)-p|)$
9:             $f(s) \leftarrow p$
10:        end for
11:    end while
12:    for each $s \in \mathcal{S}$ do $\pi(s) \leftarrow \arg\max_{a\in\mathcal{A}} r(a,s) + \sum_{s'\in succ(a,s)} p(s',a,s)f(s)$
13:    return $\pi$
14: end procedure
```

Real Time Dynamic Programming

Real Time Dynamic Programming (RTDP) is an algorithm for finding near-optimal policies for SSPP:s [2].

For SSPP:s convergence can be achieved without backing up all states. The value function will converge toward the optimal expected cost for all states reachable from the initial state under the optimal policy if the following conditions holds [2]:

- the value function is initialized to some value strictly lower than the optimal expected cost, and
- any state, that is reachable from the initial state using the policy that is greedy on the current value function, is backed up with a non-zero probability.

Consider an SSPP $\langle \mathcal{S}, \mathcal{A}, p, c, s_0, \mathcal{S}_g \rangle$. For any action $a \in \mathcal{A}$, let T_a be an operator on functions $f : \mathcal{S} \mapsto \mathbb{R}$ such that for any state s

$$T_a f(s) = c(a,s) + \sum_{s'\in succ(a,s)} p(s',s,a)f(s').$$

The RTDP algorithm explores the state space randomly through a series of *trials*, depth first random walks starting from the initial state. The RTDP algorithm is shown below as Algorithm 2. As input it is given an SSPP, a heuristic function $h : \mathcal{S} \mapsto \mathbb{R}^+$ that gives an estimate of the optimal expected cost for every state $s \in \mathcal{S}$ such that $h(s) \leq V_{\pi^*}(s)$, a time limit T_{stop} that specifies when the algorithm should halt, and a time limit T_{trial} that specifies the maximum duration of each trial.

The current policy π is undefined for states that have not been backed up. The trials (lines 10–16) are run repeatedly until the algorithm times out when $CPU\_time - t_0 \geq T_{stop}$ starting from the initial state s_0. If a state s is encountered and s has not been expanded before, then s is expanded at line 11. That is, all successor states s' are generated for all actions and s is inserted into the set G and the value function is set according to the heuristic $f(s') = h(s')$. Every encountered state s is first backed up, i.e. the current policy for that state $\pi(s)$ is selected and value function $f(s)$ is updated. Then a successor state $s' \in succ(\pi(s), s)$ is drawn randomly from the distribution $p(\cdot, s, \pi(s))$ (line 13) and the trial continues from s' through a recursive call to RUNTRIAL (line 14). If a goal state is reached or the time limit T_{trial} is reached, RTDP backtracks and backs up all the encountered states again in reverse order.

The algorithm stops when the time limit T_{stop} is reached. RTDP is guaranteed to converge toward an optimal policy as $T_{stop} \to \infty$. However, when the algorithm stops we cannot tell how close the expected cost of the obtained policy will be to the optimal expected cost.

RTDP does not need to explore every state in the state space and will therefore work even if the state space is infinite. It is sufficient that the number of actions and action outcomes in each state are finite, which is the case in a belief-MDP. Since the trials originate from the initial state s_0, the quality of the policy will tend to improve faster there. Therefore RTDP can be used as an anytime algorithm when computation time is limited [2].

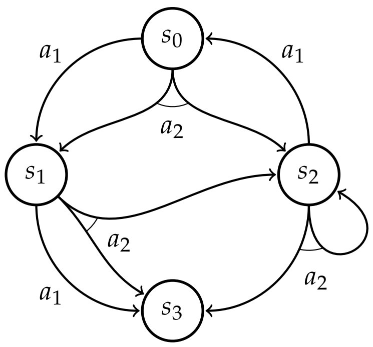
LAO*

LAO* [31] is an algorithm for finding solutions in cyclic AND/OR graphs and it can also be used to find near-optimal policies for SSPP:s. LAO* is an extension of AO* [50], a search algorithm for acyclic AND/OR graphs. This algorithm will be the basis for the new algorithm Iterative Bounding LAO* that is one of the contributions of this thesis (Chapter 4). We will therefore go through this algorithm in detail.

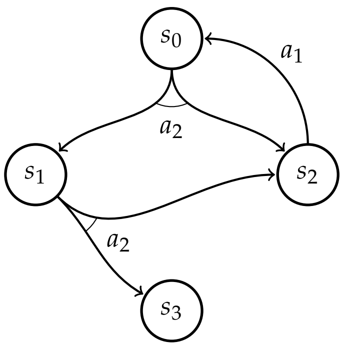
The search graph for LAO* is an AND/OR graph which can be represented as a directed hypergraph where the nodes are states and the edges correspond to actions. We can create such a graph $G = (\mathcal{N}, \mathcal{E})$ for an SSPP $\langle \mathcal{S}, \mathcal{A}, p, c, s_0, \mathcal{S}_g \rangle$ as follows. Let s_0 belong to $\mathcal{N}$ and for every state $s \in \mathcal{N} \setminus \mathcal{S}_g$ and every action $a \in \mathcal{A}$, let the states in $succ(a, s)$ also belong to $\mathcal{N}$. Also, add to $\mathcal{E}$ one outgoing edge $(s, succ(s, a))$ that leads from s to the states in $succ(s, a)$. This results in a graph where all leaves are goal states. Figure 2.6(a) shows an example of such an AND/OR graph. The hyperedges are shown as arrows

Algorithm 2 Real Time Dynamic Programming

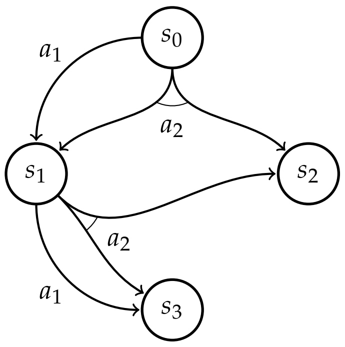
```
1:  procedure RTDP($SSPP$,$h$,$T_{stop}$,$T_{trial}$)
2:      $G \leftarrow \emptyset$
3:      $f(s_0) \leftarrow h(s_0)$
4:      $t_0 \leftarrow CPU\_time$
5:      while $CPU\_time - t_0 < T_{stop}$ do
6:          RUNTRIAL($s_0$, $CPU\_time$)
7:      end while
8:      return $\pi$
9:  end procedure

10: procedure RUNTRIAL($s$,$t$)
11:     if $s \notin G$ then EXPAND($s$)
12:     DOBACKUP($s$)
13:     $s' \leftarrow s' \sim p(\cdot, s, \pi(s))$
14:     if $s' \notin \mathcal{S}_g \wedge CPU\_time - t < T_{trial}$ then RUNTRIAL($s'$, $t_0$)
15:     DOBACKUP($s$)
16: end procedure

17: procedure EXPAND($s$)
18:     $G \leftarrow G \cup \{s\}$
19:     for each $a \in A, s' \in succ(a, s)$ do $f(s') \leftarrow h(s')$
20: end procedure

21: procedure DOBACKUP($s$)
22:     $f(s) = \min_{a \in \mathcal{A}} T_a f(s)$
23:     $\pi(s) = \arg\min_{a \in \mathcal{A}} T_a f(s)$
24: end procedure
```



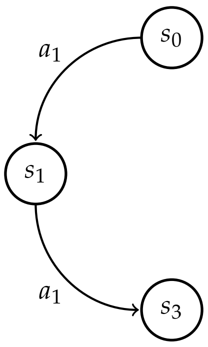
(a) The search graph G of a small SSPP.



(b) A solution graph G_π for G.



(c) A subgraph $G' \subset G$.



(d) A solution graph G'_π fpor G' where all leaves are also leaves in G thus G'_π is also a solution graph for G.

Figure 2.6: AND/OR graphs for the SSPP $\langle \{s_0, \ldots, s_3\}, \{a_1, a_2\}, p, c, s_0, \{s_3\} \rangle$
.

joined with a small arc.

A *solution graph* for a search graph G is a subgraph $G_\pi = (\mathcal{N}_\pi, \mathcal{E}_\pi)$ where $\mathcal{N}_\pi \subseteq \mathcal{N}$ and $\mathcal{E}_\pi \subseteq \mathcal{E}$ satisfying the following constraint. First, the initial state s_0 is part of G_π. Second, only states that are leaves in G can be leaves in G_π. Third, for any non-leaf s in G_π, there is exactly one outgoing hyperedge corresponding to a chosen action a to be performed in that state, and all possible successor states $succ(a, s)$ of that action belong to G_π. Figure 2.6(b) shows an example of a solution graph for the search graph shown in Figure 2.6(a).

Given a solution graph G_π, we can directly generate a policy π where for all non-goal states $s \in G_\pi \setminus \mathcal{S}_g$, the chosen action $\pi(s)$ is defined by the single outgoing hyperedge from s. Such a policy is *complete*, in the sense that it specifies an action for every non-goal state that is reachable by following the policy within G.

Now we will show how we incrementally can build a solution graph by gradually expanding a subgraph G' of G. From this solution graph we can extract a complete policy without necessarily explore all of G. Let $G' = (\mathcal{E}', \mathcal{N}')$ be an arbitrary subgraph of G containing the initial state s_0. Further, let $G'_\pi = (\mathcal{E}'_\pi, \mathcal{N}'_\pi)$ be a solution graph for G' where each non-leaf $s \in G'_\pi$ has an outgoing edge labeled with an action

$$\pi(s) = \arg\min_{a \in \mathcal{A}} T_a f(s). \tag{2.8}$$

If all leaves in G'_π are goal states, then G'_π must also be a solution graph for G and therefore corresponds to a complete policy π for G. Figure 2.6(c) shows an example of a subgraph G' to the search graph G shown in Figure 2.6(a) and Figure 2.6(d) shows an example of a solution graph for G' that is also a solution graph for G.

Since the subgraph is arbitrary, there may also be leaves that are not goal states. In this case, G'_π can be said to correspond to a partial policy π for G, which can lead to non-goal states for which no action is specified. LAO* can expand such a partial policy by specifying actions for non-goal leaves, thereby incrementally expanding G' until its solution graph is also a solution graph for G without necessarily exploring all of G.

A state s in a solution graph G'_π is evaluated with the evaluation function

$$f(s) = \begin{cases} h(s) & \text{if } s \text{ is a leaf state in } G', \\ T_{\pi(s)} f(s) & \text{otherwise,} \end{cases} \tag{2.9}$$

where $h(s)$ is an admissible heuristic estimate of the optimal expected cost such that $0 \leq h(s) \leq V_{\pi^*}(s)$. If π is a complete policy then $f(s) = V_\pi(s)$ since in each leaf, $h(s) = V_\pi(s) = 0$. It is possible to have complete policies in which it is possible to reach states from which a goal state is unreachable. However, the expected cost of such a policy is infinite.

Algorithm 3 shows the LAO* algorithm. LAO* is initialized with an explicit search graph $G' \subseteq G$ consisting only of the initial state s_0 and no hyperedges. The current policy π is initially undefined, therefore the solution graph of the explicit search graph $G'_\pi = (\mathcal{N}'_\pi, \mathcal{E}'_\pi)$ consists only of the leaf state s_0. The set $\Phi(G'_\pi)$ consists of all non-goal leaves in the current solution graph of G' that are reachable from s_0. Initially, $\Phi(G'_\pi) = \{s_0\}$ unless the initial state happens to be a goal state. The loop in lines 4–11 will ensure that eventually in G', the set $\Phi(G'_\pi) = \emptyset$, i.e. that there is eventually an action to perform for every non-goal state. Until this is the case, one or more states s in $\Phi(G'_\pi)$ are expanded (lines 5–9). Then for all actions $a \in \mathcal{A}$, the successor states $succ(s, a)$ and the corresponding hyperedges $(s, succ(a, s))$ are added to G'.

Algorithm 3 LAO*

```
 1: procedure LAO*($SSPP = \langle \mathcal{S}, \mathcal{A}, p, c, s_0, \mathcal{S}_g \rangle, \varepsilon, h$)
 2:     $G' = (\mathcal{N}', \mathcal{E}') \leftarrow (\{s_0\}, \emptyset)$
 3:     $f(s_0) \leftarrow h(s_0)$
 4:     while $\Phi(G'_\pi) \neq \emptyset$ do
 5:         $\mathcal{S}_{expand} \leftarrow \emptyset$
 6:         for some $s \in \Phi(G'_\pi)$ do
 7:             $\mathcal{S}_{expand} \leftarrow \mathcal{S}_{expand} \cup \{s\}$
 8:             EXPAND$(s)$
 9:         end for
10:         VALUEITERATION$(\langle \mathcal{S}_{expand} \cup ancestors(\mathcal{S}_{expand}), \mathcal{A}, p \rangle, 1.0, \varepsilon, f)$
11:     end while
12:     VALUEITERATION$(\langle \{s : s \in G'_\pi\}, \mathcal{A}, p \rangle, 1.0, \varepsilon, f)$
13:     if $\Phi(G'_\pi) \neq \emptyset$ then goto line 4.
14:     return $\pi$
15: end procedure

16: procedure EXPAND$(s)$
17:     for each $a \in \mathcal{A}$ do
18:         for each $s' \in succ(a, s) \setminus \mathcal{N}'$ do
19:             $f(s') = h(s')$
20:         end for
21:         $\mathcal{N}' \leftarrow \mathcal{N}' \cup succ(a, s)$
22:         $\mathcal{E}' \leftarrow \mathcal{E}' \cup (s, succ(a, s))$
23:     end for
24: end procedure
```

After the expansions, (2.9) is evaluated for all the newly expanded states in $\mathcal{S}_{expand}$ and their $ancestors(\mathcal{S}_{expand})$ using the Value Iteration algorithm in line 10. Value Iteration updates both the value function f and the current policy π for these states.

When $\Phi(G'_\pi) = \emptyset$, then in line 12 LAO* performs value iteration again, this time over all states in $\mathcal{N}'_\pi$ until either the f-values converge or some non-goal state appears among the leaf states of G'_π in which case LAO* goes back to line 4. When all leaves in G'_π are goal states and the f-values have properly converged by Value Iteration, $\Phi(G'_\pi) = \emptyset$ and $V_\pi - V_{\pi^*} < \epsilon$ in line 14.

2.3.5 Finding the Optimal Policy for a POMDP

Finding an optimal policy for a POMDP is much more difficult than for an MDP with a finite state space of equal size. However, in certain situations a POMDP may be solved more efficiently than the corresponding belief-MDP which has a much larger state space.

If we are interested in finding plans with a fixed depth T, the value function (2.5) of an optimal policy can be represented by a piecewise linear function. This is used by several POMDP algorithms. Instead of representing the optimal value function as a vector over states, the optimal T-step policy is represented with a set of linear constraints Υ_T on the belief space $\mathcal{B}$. Each constraint is a pair $\langle a, V_T \rangle$ where a is the first action of some T-step policy and V_T is a vector specifying the expected reward of that policy for each state $s \in \mathcal{S}$. The optimal T-step policy is extracted from Υ_T as

$$\pi^*_T(b) = \underset{\langle a, V_T \rangle \in \Upsilon_T}{\arg\max} \sum_{s \in \mathcal{S}} b(s) V_T(s).$$

Initially the set of constraints Υ_1 consists of one constraint $\langle a, V_1 \rangle$ for every action $a \in A$ where $V_1(s) = r(a, s)$ for every state $s \in A$. We can compute the next set of constraint Υ_{T+1} from a previous set of constraints Υ_T and thereby obtain optimal policies of any length. Let $\mathcal{V}_T$ be a function $\mathcal{O} \mapsto \Upsilon_T$, and let $\Omega_{\mathcal{V}_T}$ be the set of all possible such functions. The next set of constraints Υ_{T+1} can then be obtained from the previous one by adding a constraint $\langle a, V_{T+1} \rangle$ for every $a \in \mathcal{A}$ and every $\mathcal{V}_T \in \Omega_{\mathcal{V}_T}$ where

$$V_{T+1}(s) = r(a, s) + \gamma \sum_{o \in \mathcal{O}} \Big(\omega(o, s, a) \sum_{s' \in succ(a,s)} p(s', s, a) \mathcal{V}_T(o)(s') \Big).$$

By letting $T \to \infty$ the expected reward for an optimal infinite horizon POMDP policy can be approximated with arbitrary precision. If this is done naively, the size of Υ_T would be $|\mathcal{A}|^{\frac{|\mathcal{O}|^T - 1}{|\mathcal{O}| - 1}}$. However, not every constraint in Υ_T is needed. Every constraints that is dominated by some other constraint in each point in $b \in \mathcal{B}$ can be removed.

State of the art POMDP solvers vary in the way in which they remove constraints from Υ_T. For example, Point-Based Value Iteration (PBVI) [59] removes all constraints that are dominated by some other constraint in a limited set of belief states in the belief space. This is an approximation because a removed constraint could be the dominating constraint in belief states outside this limited set of belief states.

Another algorithm, Heuristic Search Value Iteration (HSVI) [75], removes only those constraints that are point-wise dominated by some other constraint.

This guarantees that no constraint from the optimal set of constraints is removed.

Part II

Decision-Theoretic Troubleshooting of Heavy Vehicles

3

Troubleshooting Framework

This chapter is on the framework for troubleshooting described in Section 1.4. We will formally define the troubleshooting model and the troubleshooting problem in Sections 3.2 and 3.3. We will also define a set of assumptions that can be applied when modeling the troubleshooting process for heavy vehicles in Section 3.4. When describing the Diagnoser in Section 3.5 we will present a new way to represent and use the non-stationary Dynamic Bayesian Networks for troubleshooting. In Section 3.6 we present the Planner. There we will show how the troubleshooting problem can be modeled and solved as a Stochastic Shortest Path Problem (SSPP). Many solvers for SSPP:s benefit from using search heuristics. New heuristics applicable for the troubleshooting problem are presented in Section 3.6.3. In Section 3.6.4 we will show how certain actions can grouped together to make the planning process more efficient without losing optimality. In Section 3.7 we will study what the consequences will be if we relax some of the assumptions previously made in Section 3.4, thus creating a more general framework.

3.1 Small Example

Here we will introduce a small sample system that is used to demonstrate some of the concepts of the modeling, inference and planning in the troubleshooting framework. The example will be incrementally expanded as more concepts are

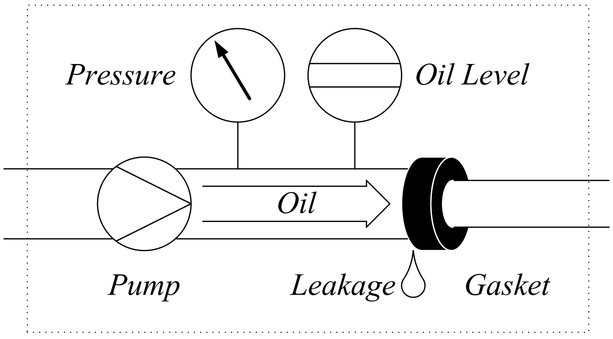


Figure 3.1: Schematic of example system.

introduced.

In the sample system (Figure 3.1), oil is pumped through a pipe connected to a smaller pipe through a gasket. The system includes an oil pressure sensor and a dipstick to check the oil level. There are four different faults which may cause the system to fail. In case of a *pump failure*, nominal pressure cannot be maintained. This will also happen if the *oil level* is too low. In case of a *leaking gasket*, the oil level will fall. However the oil level can also be low for other unknown reasons. Leaking oil from a faulty gasket may or may not be visible on the outside of the pipe. When the pressure is low, a low pressure alarm is raised. This alarm will also be triggered in case of a fault in the *pressure sensor*.

A mechanic that is troubleshooting this system may repair the system by re-filling the oil, repairing the oil pump, or replacing the gasket or the oil pressure sensor. Also, the mechanic may gain additional information of the system by observing the oil level, searching for a visible leakage or inspecting the pump. To reach the pipe an outer protective casing must be removed. This must be done before performing any action on the pump or gasket. Also, to replace the gasket the smaller pipe must be removed. To test the system and see if a low pressure alarm is triggered the entire system must be assembled.

3.2 The Troubleshooting Model

Parts of the system that may fail, i.e., components such as sensors, actuators, wiring, and pipes, are modeled with variables called *component variables*. Parts of the system that may affect when an action can be performed, such as the protective casings around components that must be removed before certain actions can be performed, are modeled with variables called *feature variables*.

The same component can be modeled with both a component variable and a feature variable since they model different aspects of the component. A component variable models a component's "health", e.g., whether the component is faulty or not, while a feature variable models a component's "position", e.g., whether the component is in place or removed. Variables called *observation variables* are used to model observable quantities such as the readings from sensors and alarms from the ECU:s.

The troubleshooting model for any given system consists of these variables and also the model contains information regarding how the values of the variables depend on each other and which actions that can be performed on the system.

Definition 3.1 (Troubleshooting model)**.** The *troubleshooting model* is a tuple

$$M = \langle \mathbf{C}, \mathbf{O}, \mathbf{F}, \mathcal{A}, M_P \rangle \tag{3.1}$$

where:

- The set $\mathbf{C}$, the *component variables*, consists of stochastic variables representing the health of components. Each component variable $C \in \mathbf{C}$ must be in one fault mode c. and one of the fault modes is the no fault case NF.

- The set $\mathbf{O}$, the *observation variables*, consists of stochastic variables representing possible observations that can be made on the system. Each observation variable $O \in \mathbf{O}$ must be in one observation mode o.

- The set $\mathbf{F}$, the *feature variables*, consists of non-stochastic variables representing parts of the system that may constrain which actions can be performed. Each feature variable $F \in \mathbf{F}$ must be in one feature mode f. To be able to perform certain actions, certain feature variables must be in specific modes.

- The set $\mathcal{A}$ consists of the actions that may be performed. The actions are described further in Section 3.2.1.

- The probabilistic dependency model M_P is a diagnostic model that describes the probabilistic dependencies between components, observations and actions over time. This model is described further in Section 3.2.2.

□

Example 3.1 (Components, Observations, and Features of the Sample System)**.** From the description of the sample system in Section 3.1, the components, observations and features can be modeled as follows:

Variable		Type	Modes
C_1	Pump	Component	$\{NF, failure\}$
C_2	Gasket	Component	$\{NF, leaking\}$
C_3	Pressure Sensor	Component	$\{NF, failure\}$
C_4	Oil Level	Component	$\{NF, low\}$
O_1	Visible Leakage	Observation	$\{no, yes\}$
O_2	Low Oil Pressure	Observation	$\{normal, low\}$
O_3	Low Oil Pressure Alarm	Observation	$\{not\ indicating, indicating\}$
F_1	Outer Casing	Feature	$\{fitted, removed\}$
F_2	Small Pipe	Feature	$\{fitted, removed\}$

3.2.1 Actions

We define actions similarly to ground planning operators, with precondition, effects and cost. For an action $a \in \mathcal{A}$, the precondition $\mathcal{F}_a \subseteq \Omega_{\mathbf{F}}$ defines a set of possible assignments of the feature variables such that if $\mathbf{F} = \mathbf{f}$ and $\mathbf{f} \in \mathcal{F}_a$, we are allowed to perform a. An action may have zero or more effects that are ordered in a sequence. The effects can be:

- to repair a component $repair(C)$,
- to change the mode of a feature $F := f$,
- to observe the mode of an observation $obs(O)$ or a component $obs(C)$, or
- to operate system for a duration of τ time units $operate(\tau)$.

The cost of an action a is real-valued constant c_a.

The action a_0 is a special *stop action* that has no effects and zero cost. It is used to indicate that the troubleshooting is complete and no more actions should be performed. All other actions must have at least one effect.

Events

When an action is performed on the system in the real world an *event* is generated for each effect. A sequence of events represents an outcome of the action and it is dependent on how the system responds so we cannot always know in advance which the event will be. Unless stated otherwise, time is assumed discrete and increases by 1 for each discrete event that occurs. When an action $a \in \mathcal{A}$ that has n_a effects is performed at time t, an event sequence $\mathbf{E}_a^t = \mathbf{e}^{t:t+n_a-1}$ is generated.

For a repair effect $repair(C)$, the generated event is $C^t := NF$ which means that the variable C is forced into the mode NF at time t independently of the mode of C at time $t-1$. An effect that changes the mode of a feature variable $F{:=}f$ is treated similarly and the event $F^t{:=}f$ is generated. An operation effect $\mathit{operate}(\tau)$ generates an operation event $\omega^t(\tau)$. For an observe effect $\mathit{obs}(O)$, one of $|\Omega_O|$ different events is generated depending on the response from the system. The event $O^t = o$ means that the variable O is observed to be in the mode o at time t, e.g. at time t the effect $\mathit{obs}(O_2)$ generates one of the events $O_2^t = \mathit{normal}$ and $O_2^t = \mathit{low}$.

The value of the feature variables will not be affected by any other event than those of the type $F{:=}f$. After the occurrence of such an event at time t, we can trivially infer the values of the feature variables at time t given their value at time $t-1$. We indicate this by writing $e^t \wedge \mathbf{F}^{t-1} \vdash \mathbf{F}^t$ where $e^t = \{F_i^t := f_i'\}$ is the event that results from assigning the value f_i' to the feature F_i at time t, $\mathbf{F}^{t-1} = [f_1, \ldots, f_n]$ is a sequence specifying all feature values at the preceding time step $t-1$, and $\mathbf{F}^t = [f_1, \ldots, f_{i-1}, f_i', f_{i+1}, \ldots, f_n]$ is the same sequence with a new value for the modified feature F_i.

Example 3.2 (Actions of Sample System)**.** Below are the actions for the sample system introduced in Section 3.1. The costs are values that reflect the time to execute the action and the costs of resources consumed when performing the action. When any of the actions that repair components (a_1–a_4) or change feature modes (a_9–a_{12}) are performed, a single event corresponding to the effect is generated with certainty. When an observing action (a_5–a_8) is performed, one of two events may be generated. For example if the action a_7 *Check Visible Leakage* is performed, the generated event may either be $O_1 = \mathit{no}$ or $O_1 = \mathit{yes}$.

Action		Precondition	Effects	Cost
a_0	Stop	$F_1 = \mathit{fit.} \wedge F_2 = \mathit{fit.}$	$\{\}$	0
a_1	Repair Pump	$F_1 = \mathit{rem.}$	$\{\mathit{repair}(C_1)\}$	150
a_2	Replace Gasket	$F_2 = \mathit{rem.}$	$\{\mathit{repair}(C_2)\}$	15
a_3	Replace Pres. Sensor		$\{\mathit{repair}(C_3)\}$	100
a_4	Fill Oil	$F_2 = \mathit{fit.}$	$\{\mathit{repair}(C_4)\}$	20
a_5	Inspect Pump	$F_1 = \mathit{rem.}$	$\{\mathit{obs}(C_1)\}$	10
a_6	Check Oil Level	$F_2 = \mathit{fit.}$	$\{\mathit{obs}(C_4)\}$	10
a_7	Check Visible Leakage	$F_1 = \mathit{rem.} \wedge F_2 = \mathit{fit.}$	$\{\mathit{obs}(O_1)\}$	10
a_8	Test System	$F_1 = \mathit{fit.}$	$\{\mathit{obs}(O_3)\}$	40
a_9	Remove Casing	$F_1 = \mathit{fit.}$	$\{F_1 := \mathit{rem.}\}$	25
a_{10}	Fit Casing	$F_1 = \mathit{rem.} \wedge F_2 = \mathit{fit.}$	$\{F_1 := \mathit{fit.}\}$	25
a_{11}	Remove Pipe	$F_1 = \mathit{rem.} \wedge F_2 = \mathit{fit.}$	$\{F_2 := \mathit{rem.}\}$	40
a_{12}	Fit Pipe	$F_2 = \mathit{rem.}$	$\{F_2 := \mathit{fit.}\}$	40

3.2.2 Probabilistic Dependency Model

The probabilistic dependency model provides a model for the distributions $P(\mathbf{C}_0, \mathbf{O}_0)$, $P(\mathbf{C}^t, \mathbf{O}^t | \mathbf{C}^0, \mathbf{O}^0, \mathbf{E}^{1:t})$ and $P(\mathbf{E}^{t+1} | \mathbf{C}^0, \mathbf{O}^0, \mathbf{E}^{1:t})$ for all $t \in \mathbb{N}^+$. The distributions of $\mathbf{C}^t$, $\mathbf{O}^t$ and $\mathbf{E}^{t+1}$ are only dependent on the prior distribution $P(\mathbf{C}_0, \mathbf{O}_0)$ and all events up to time t, $\mathbf{E}^{1:t}$. The probabilistic dependency model can, as in this thesis, be realized using non-stationary Dynamic Bayesian Networks (nsDBN:s) that are described in Section 2.2.3.

Example 3.3 (Probabilistic Model of Sample System)**.** In the sample system, components do not spontaneously break during troubleshooting and observations are only dependent on the mode of the components. Therefore, in the nsDBN, all component variables are modeled as *persistent* variables and and all observation variables are modeled as *non-persistent*. The initial nsDBN is shown in Figure 3.2.

In this BN C_1–C_3 have no parents and $P(C_1 \neq NF) = 0.001$, $P(C_2 \neq NF) = 0.001$, and $P(C_3 \neq NF) = 0.004$. This means that the Oil Pressure Sensor fails four times as often as the pump and the gasket.

The oil level will be drained if the Gasket is leaking, so $P(C_4 = low | C_2 = leaking) = 1$. The oil level may also be low for other unknown reasons and therefore $P(C_4 = low | C_2 = NF) = 0.002$. The dependency between C_4 and C_2 is modeled as *non-instant* since changes in the mode of the gasket will not have an instantaneous effect on the oil level.

If the pump is working and the oil level is normal, the oil pressure should be normal. However, if either the pump fails or the oil level becomes low, then pressure will be lost. This is modeled as $P(O_2 = low | C_1 = NF, C_4 = NF) = 0$ and $P(O_2 = low | C_1 \neq NF \vee C_4 \neq NF) = 1$. Assuming that a pump breakdown or a loss of oil immediately causes the pressure to drop these dependencies are modeled as *instant*.

The low oil pressure alarm will trigger if either the oil pressure is low or the pressure sensor fails, i.e. $P(O_3 = indicating | C_3 = failure \vee O_2 = low) = 1$ and $P(O_3 = indicating | C_3 = NF, O_2 = normal) = 0$. These dependencies are also *instant*.

Visible leakage is modeled as a *non-instant* dependency where $P(O_1 = yes | C_2 = leaking) = 0.9$ and $P(O_1 = yes | C_2 = NF) = 0$. This means that the leakage is not always visible from the outside and it is required that the vehicle is operated for the leakage to appear.

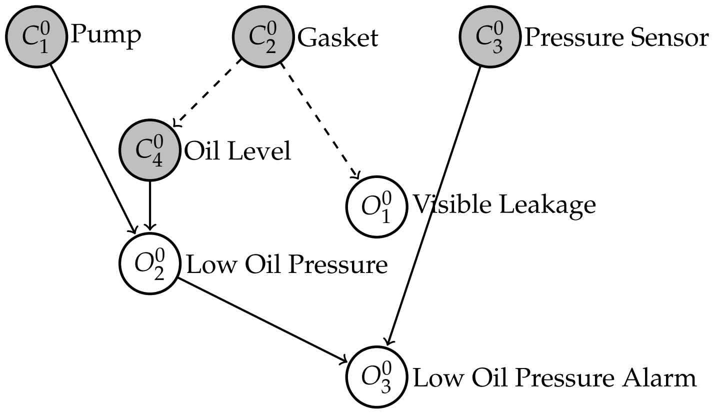


Figure 3.2: Initial non-stationary Dynamic Bayesian Network of the sample system. Persistent variables are shaded and non-instant edges are dashed.

3.3 The Troubleshooting Problem

Definition 3.2 (Troubleshooting problem). A *troubleshooting problem* is represented by the tuple

$$I = \langle M, \mathbf{e}^{1:t}, \mathbf{f}^0, \mathcal{F}_g, \mathcal{C}_g \rangle \tag{3.2}$$

where M is the troubleshooting model, $\mathbf{e}^{1:t}$ are all events that have happened up to the current time t, $\mathbf{f}^0$ are the feature modes the system initially is in and $\mathcal{F}_g \subseteq \Omega_{\mathbf{F}}$ and $\mathcal{C}_g \subseteq \Omega_{\mathbf{C}}$ are the modes all feature and component variables should be in when troubleshooting is complete. □

3.3.1 Troubleshooting Plans

A solution to the troubleshooting problem is a conditional plan of actions that can be followed to successfully repair any faulty component. The troubleshooting plan is a function that tells what action to do next given the sequence of events that has occurred.

Definition 3.3 (Troubleshooting Plan). Let $I = \langle M, \mathbf{e}^{1:t_c}, \mathbf{f}^0, \mathcal{F}_g, \mathcal{C}_g \rangle$ be a troubleshooting problem where t_c is the current time and let $\mathcal{E}_\pi$ be a set of sequences of events specific to a *troubleshooting plan* π that is a a function $\pi : \mathcal{E}_\pi \mapsto \mathcal{A}$ where all of the following holds:

1) $\mathbf{e}^{1:t_c} \in \mathcal{E}_\pi$, i.e., the plan has an action for the sequence of events that has occurred up to the current time,

2) for all $\mathbf{e}^{1:t} \in \mathcal{E}_\pi$ and all $\mathbf{e}^{t+1:t+n_{\pi(\mathbf{e}^{1:t})}} \in \mathbf{E}^{t+1}_{\pi(\mathbf{e}^{1:t})}$, the sequence $\mathbf{e}^{1:t}; \mathbf{e}^{t+1:t+n_{\pi(\mathbf{e}^{1:t})}}$ is also in $\mathcal{E}_\pi$, i.e., for all sequences of events $\mathbf{e}^{1:t}$ already in $\mathcal{E}_\pi$, the plan has an action for every outcome of the action $\pi(\mathbf{e}^{1:t})$,

3) for all $\mathbf{e}^{1:t} \in \mathcal{E}_\pi$, it is the case that $\mathbf{e}^{1:t} \wedge \{\mathbf{F}^0 = \mathbf{f}^0\} \vdash \{\mathbf{F}^t = \mathbf{f}\}$ for some $\mathbf{f} \in \mathcal{F}_{\pi(\mathbf{e}^{1:t})}$, i.e., if the plan has an action for a sequence of events $\mathbf{e}^{1:t}$, then the preconditions of that action $\mathcal{F}_{\pi(\mathbf{e}^{1:t})}$ are satisfied given the status of the feature variables at time t.

□

A troubleshooting plan π is said to be a *solution* to the troubleshooting problem $I = \langle M, \mathbf{e}^{1:t_c}, \mathbf{f}^0, \mathcal{F}_g, \mathcal{C}_g \rangle$ if for every $\mathbf{e}^{1:t} \in \mathcal{E}_\pi$ where $\pi(\mathbf{e}^{1:t}) = a_0$, it holds that $P(\mathbf{C}^t \in \mathcal{C}_g | \mathbf{e}^{1:t}, M) = 1$ and $\mathbf{e}^{1:t} \wedge \{\mathbf{F}^0 = \mathbf{f}^0\} \vdash \{\mathbf{F}^t = \mathbf{f}\}$ for same $\mathbf{f} \in \mathcal{F}_g$. This means that the stop action will only be executed when the troubleshooting goals are achieved.

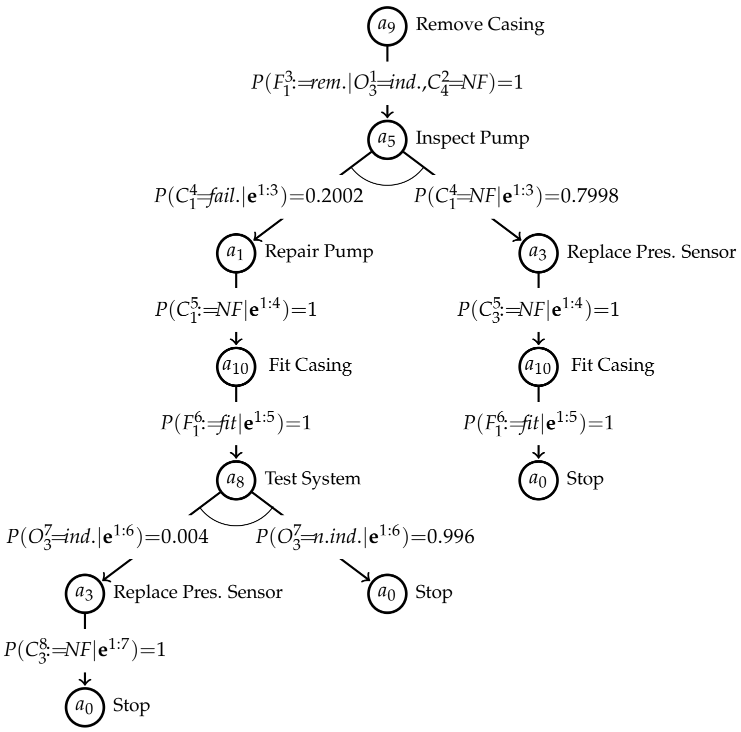
A troubleshooting plan can be seen as a tree where the nodes are actions and edges are events. The leaves of this tree are stop actions because the stop action is the only action that has no effects and therefore generates no events.

Example 3.4. Let M_{ex} be the sample system modeled in Section 3.2. Consider an instance of the troubleshooting problem I where the low oil pressure alarm has been triggered and it has been observed that the oil level is normal:

$$I_{\text{ex}} = \langle M_{\text{ex}}, (O_3^1 = \textit{ind.}, C_4^2 = \textit{NF}), (\textit{fit.}, \textit{fit.}), \{(\textit{fit.}, \textit{fit.})\}, \{(\textit{NF}, \textit{NF}, \textit{NF}, \textit{NF})\} \rangle.$$

Figure 3.3 shows a graphical representation of a troubleshooting plan π_{ex} that is a solution to the problem I_{ex}. Written out, π_{ex} is the following:

Action	Sequence of events
a_9	$(O_3^1 = \text{ind.}, C_4^2 = \textit{NF})$
a_5	$(O_3^1 = \text{ind.}, C_4^2 = \textit{NF}, F_1^3 := \textit{rem.})$
a_3	$(O_3^1 = \text{ind.}, C_4^2 = \textit{NF}, F_1^3 := \textit{rem.}, C_1^4 = \textit{NF})$
a_{10}	$(O_3^1 = \text{ind.}, C_4^2 = \textit{NF}, F_1^3 := \textit{rem.}, C_1^4 = \textit{NF}, C_3^5 := \textit{NF})$
a_0	$(O_3^1 = \text{ind.}, C_4^2 = \textit{NF}, F_1^3 := \textit{rem.}, C_1^4 = \textit{NF}, C_3^5 := \textit{NF}, F_1^6 := \textit{fit.})$
a_1	$(O_3^1 = \text{ind.}, C_4^2 = \textit{NF}, F_1^3 := \textit{rem.}, C_1^4 = \textit{fail.})$
a_{10}	$(O_3^1 = \text{ind.}, C_4^2 = \textit{NF}, F_1^3 := \textit{rem.}, C_1^4 = \textit{fail.}, C_1^5 := \textit{NF})$
a_8	$(O_3^1 = \text{ind.}, C_4^2 = \textit{NF}, F_1^3 := \textit{rem.}, C_1^4 = \textit{fail.}, C_1^5 := \textit{NF}, F_1^6 := \textit{fit.})$
a_0	$(O_3^1 = \text{ind.}, C_4^2 = \textit{NF}, F_1^3 := \textit{rem.}, C_1^4 = \textit{fail.}, C_1^5 := \textit{NF}, F_1^6 := \textit{fit.}, O_3^7 = \text{n.ind.})$
a_3	$(O_3^1 = \text{ind.}, C_4^2 = \textit{NF}, F_1^3 := \textit{rem.}, C_1^4 = \textit{fail.}, C_1^5 := \textit{NF}, F_1^6 := \textit{fit.}, O_3^7 = \text{ind.})$
a_0	$(O_3^1 = \text{ind.}, C_4^2 = \textit{NF}, F_1^3 := \textit{rem.}, C_1^4 = \textit{fail.}, C_1^5 := \textit{NF}, F_1^6 := \textit{fit.}, O_3^7 = \text{ind.}, C_3^8 := \textit{NF})$



a_9 Remove Casing
$P(F_1^3{:}{=}rem.|O_3^1{=}ind.,C_4^2{=}NF)=1$
a_5 Inspect Pump
$P(C_1^4{=}fail.|\mathbf{e}^{1:3})=0.2002$
$P(C_1^4{=}NF|\mathbf{e}^{1:3})=0.7998$
a_1 Repair Pump
a_3 Replace Pres. Sensor
$P(C_1^5{:}{=}NF|\mathbf{e}^{1:4})=1$
$P(C_3^5{:}{=}NF|\mathbf{e}^{1:4})=1$
a_{10} Fit Casing
a_{10} Fit Casing
$P(F_1^6{:}{=}fit|\mathbf{e}^{1:5})=1$
$P(F_1^6{:}{=}fit|\mathbf{e}^{1:5})=1$
a_8 Test System
a_0 Stop
$P(O_3^7{=}ind.|\mathbf{e}^{1:6})=0.004$
$P(O_3^7{=}n.ind.|\mathbf{e}^{1:6})=0.996$
a_3 Replace Pres. Sensor
a_0 Stop
$P(C_3^8{:}{=}NF|\mathbf{e}^{1:7})=1$
a_0 Stop

Figure 3.3: A troubleshooting plan for the sample system. +++ förstora!

3.3.2 Troubleshooting Cost

Let π be a troubleshooting plan for a troubleshooting problem where the sequence of events that has occurred is $\mathbf{e}^{1:t}$. The cost of repair CR is the cost of performing a sequence of actions in π starting with $\pi(\mathbf{e}^{1:t})$ until the stop action is encountered. This yields a possibly infinite sequence of events $\mathbf{e}^{1:\infty}$. This sequence is not known until after the plan is executed since the events are stochastic and we cannot for certain know the outcomes of the actions in advance.

$$CR(\pi, \mathbf{e}^{1:\infty}, t) = \sum_{i=t}^{\infty} \mathbb{1}_{\mathcal{E}_\pi}(\mathbf{e}^{1:i}) c_{\pi(\mathbf{e}^{1:i})}. \tag{3.3}$$

where t is the time when the plan starts and $\mathbb{1}_{\mathcal{E}_\pi}$ is an indicator function for the set $\mathcal{E}_\pi$, i.e. $\mathbb{1}_{\mathcal{E}_\pi}(\mathbf{e}) = 1$ if $\mathbf{e} \in \mathcal{E}_\pi$ and zero otherwise. The indicator function is needed because actions may generate multiple events, so there may be multiple time steps between action invocations. For example, if an action a that has three effects is invoked at time $t = 10$, the next action after a is invoked at time $t = 13$. Then, the plan will not be defined for the sequences of events $\mathbf{e}^{1:11}$ or $\mathbf{e}^{1:12}$.

We cannot compute the cost of repair in advance, but we still want to be able to prioritize between different plans. Therefore, we are interested in the *expected cost of repair*.

Let $\mathbf{E}_{\pi,\mathbf{e}^{1:t}}$ be stochastic variables where the outcome space $\Omega_{\mathbf{E}_{\pi,\mathbf{e}^{1:t}}}$ is a subset of $\mathcal{E}_\pi$ such that for each $\mathbf{e}' \in \Omega_{\mathbf{E}_{\pi,\mathbf{e}^{1:t}}}$, $\mathbf{e}^{1:t}$ is a prefix of $\mathbf{e}'$ and no $\mathbf{e}'' \in \mathcal{E}_\pi$ exist such that $\mathbf{e}'$ is strict prefix of $\mathbf{e}''$. I.e., the outcome space of $\mathbf{E}_{\pi,\mathbf{e}^{1:t}}$ consists of the sequences of events generated from every possible longest path in π beginning with $\mathbf{e}^{1:t}$. The probability distribution of $\mathbf{E}_{\pi,\mathbf{e}^{1:t}}$ given the sequence of events generated so far $\mathbf{e}^{1:t}$ and the probabilistic dependency model M_P is

$$P(\mathbf{E}_{\pi,\mathbf{e}^{1:t}} = \mathbf{e}^{1:\infty} | \mathbf{e}^{1:t}, \pi, M_P) = \prod_{i=t}^{\infty} P(e^{i+1} | \mathbf{e}^{1:i}, \pi, M_P). \tag{3.4}$$

The expected cost of repair ECR of a troubleshooting plan π after the events $\mathbf{e}^{1:t}$ have occurred is the expected value of $CR(\pi, \mathbf{E}_{\pi,\mathbf{e}^{1:t}}, t)$:

$$\begin{aligned} ECR(\pi, \mathbf{e}^{1:t}) &= E(CR(\pi, \mathbf{E}_{\pi,\mathbf{e}^{1:t}}, t) | \mathbf{e}^{1:t}, M_P) \\ &= \sum_{\bar{\mathbf{e}} \in \mathbf{E}_{\pi,\mathbf{e}^{1:t}}} P(\bar{\mathbf{e}} | \mathbf{e}^{1:t}, \pi, M_P) CR(\pi, \bar{\mathbf{e}}, t) \end{aligned} \tag{3.5}$$

Let $\mathbf{E}_a$ be the set of events that may be generated when the action a is performed and let n_a be the number of events generated by a. Using (3.3) and (3.4), the expected cost of repair (3.5) can be reformulated into recursive form as

$$\begin{aligned}
ECR(\pi, \mathbf{e}^{1:t}) &= \sum_{\bar{\mathbf{e}} \in \mathbf{E}_{\pi,\mathbf{e}^{1:t}}} P(\bar{\mathbf{e}}|\mathbf{e}^{1:t}, \pi, M_P) CR(\pi, \bar{\mathbf{e}}, t) \\
&= \sum_{\bar{\mathbf{e}} \in \mathbf{E}_{\pi,\mathbf{e}^{1:t}}} P(\bar{\mathbf{e}}|\mathbf{e}^{1:t}, \pi, M_P) \big(c_{\pi(\mathbf{e}^{1:t})} + CR(\pi, \bar{\mathbf{e}}, t+n_\pi(\mathbf{e}^{1:t}))\big) \\
&= c_{\pi(\mathbf{e}^{1:t})} + \\
&\quad + \sum_{\mathbf{e}' \in \mathbf{E}_{\pi(\mathbf{e}^{1:t})}} P(\mathbf{e}'|\mathbf{e}^{1:t}, \pi(\mathbf{e}^{1:t}), M_P) \sum_{\bar{\mathbf{e}} \in \mathbf{E}_{\pi,\mathbf{e}^{1:t};\mathbf{e}'}} P(\bar{\mathbf{e}}|\mathbf{e}^{1:t};\mathbf{e}', \pi, M_P) CR(\pi, \bar{\mathbf{e}}, t+n_{\pi(\mathbf{e}^{1:t})}) \\
&= c_{\pi(\mathbf{e}^{1:t})} + \sum_{\mathbf{e}' \in \mathbf{E}_{\pi(\mathbf{e}^{1:t})}} P(\mathbf{e}'|\mathbf{e}^{1:t}, \pi(\mathbf{e}^{1:t}), M_P) ECR(\pi, \mathbf{e}^{1:t}; \mathbf{e}') \qquad (3.6)
\end{aligned}$$

Example

By using (3.6) repeatedly and inserting the values for the action costs from Example 3.2, the expected cost of repair for the troubleshooting plan π_{ex} in Figure 3.3 can be computed to be approximately 178.1:

$$\begin{aligned}
&ECR(\pi_{\text{ex}}, (O_3^1 = ind, C_4^2 := NF)) = c_{a_9} + ECR(\pi_{\text{ex}}, (O_3^1 = ind, C_4^2 := NF, F_1^3 := rem)) \\
&\quad = c_{a_9} + \Big(c_{a_5} + \sum_{e \in \{C_1^4 = NF, C_1^4 = F\}} \Big(P(e|(O_3^1 = ind, C_4^2 := NF, F_1^3 := rem), M_P) \\
&\qquad\qquad ECR(\pi_{\text{ex}}, (O_3^1 = ind, C_4^2 := NF, F_1^3 := rem, e))\Big)\Big) \\
&\quad = \ldots \approx 178.1
\end{aligned}$$

Optimal Troubleshooting Plans

The optimal expected cost of repair ECR^* for a troubleshooting problem $I = \langle M, \mathbf{e}^{1:t}, \mathbf{f}^0, \mathcal{F}_g, \mathcal{C}_g \rangle$ is

$$\begin{aligned}
ECR^*(\mathbf{e}^{1:t}) &= \min_{\pi^* \in \Pi(I)} ECR(\pi^*, \mathbf{e}^{1:t}) \\
&= \min_{\pi^* \in \Pi(I)} c_{\pi^*(\mathbf{e}^{1:t})} + \sum_{\bar{\mathbf{e}} \in \mathbf{E}_{\pi(\mathbf{e}^{1:t})}} P(\bar{\mathbf{e}}|\mathbf{e}^{1:t}, \pi^*(\mathbf{e}^{1:t}), M_P) ECR(\pi^*, \mathbf{e}^{1:t}; \bar{\mathbf{e}}) \\
&= \min_{\pi^* \in \Pi(I)} c_{\pi^*(\mathbf{e}^{1:t})} + \sum_{\bar{\mathbf{e}} \in \mathbf{E}_{\pi(\mathbf{e}^{1:t})}} P(\bar{\mathbf{e}}|\mathbf{e}^{1:t}, \pi^*(\mathbf{e}^{1:t}), M_P) ECR^*(\mathbf{e}^{1:t}; \bar{\mathbf{e}}) \qquad (3.7)
\end{aligned}$$

where $\Pi(I)$ is the set of all troubleshooting plans that are solutions to I.

An optimal troubleshooting plan π^* is a solution to I and $ECR(\pi^*, \mathbf{e}^{1:t}) = ECR^*(\mathbf{e}^{1:t})$. The actions of π^* are

$$\pi^*(\mathbf{e}^{1:t}) = \arg\min_{a \in \mathcal{A}_{\mathbf{e}^{1:t}}} c_{\pi(\mathbf{e}^{1:t})} + \sum_{\bar{\mathbf{e}} \in \mathbf{E}_{\pi(\mathbf{e}^{1:t})}} P(\bar{\mathbf{e}}|\mathbf{e}^{1:t}, a, M_P) ECR^*(\mathbf{e}^{1:t}; \bar{\mathbf{e}}) \qquad (3.8)$$

where the set $\mathcal{A}_{\mathbf{e}^{1:t}} \subseteq \mathcal{A}$ consists of all actions that have their preconditions satisfied given $\mathbf{e}^{1:t}$.

3.4 Assumptions

This section contains a list of assumptions that can be made for the troubleshooting problem. The assumptions can be exploited for a faster and more efficient solution. For many of these assumptions, we will also show how the troubleshooting problem can be solved when the assumptions do not apply in Section 3.7.

3.4.1 Assumptions for the Problem

Assumption 1 (Repair Goal)**.** All faulty components must be repaired.

Assumption 1 is reasonable because it states that the troubleshooting task is the same as stated in the problem formulation in Section 1.2.

3.4.2 Assumptions for the Action Model

Assumption 2 (Repairable Components)**.** For each component $C \in \mathbf{C}$ there exists at least one action that generates the event $C := NF$.

If Assumption 1 is made, but not Assumption 2, then the repair goal may not be achievable because some components cannot be repaired.

Assumption 3 (Perfect repair)**.** An action that attempts to repair a component will succeed in doing so with probability 1.

Assumption 3 is valid for systems where the typical repair action is to replace a faulty component with a brand new one. This assumption is not applicable for systems where the components are sensitive and there is a risk that they are damaged upon replacement or where repairs are difficult and attempted repairs may fail.

Assumption 4 (Satisfiable preconditions)**.** All actions have preconditions that are such that for every possible mode the feature variables can be in, there exist some sequence of actions that satisfies those preconditions. Also, every such sequence is such that no non-faulty component is caused to become faulty with certainty.

If Assumption 4 is not made, there could be actions that never could be performed and components that cannot be repaired.

Assumption 5 (Assembly modes)**.** Each feature variable has only two feature modes, *assembled mode A* or *disassembled mode D*.

Assumption 5 is applicable for systems where the feature variables represent parts of the system that may be physically obstructing other parts of the system so that an action cannot be performed, e.g. a cover or a part that needs to be disassembled to expose the components of which the part is composed. Note that the modes of a feature variable may have different names, e.g. the feature variable "Outer Casing" in the example has the assembled mode is called "fitted" and the disassembled mode is called "removed".

Assumption 6 (Dependencies between feature variables)**.** An action causing $F := D$ only has preconditions requiring other features to be disassembled and F to be assembled. An action causing $F := A$ only has preconditions requiring other features to be assembled and F to be disassembled. Furthermore, the dependencies between features are acyclic in the sense that disassembling one feature cannot (directly or recursively) require the feature to already be disassembled, and similarly for assembling a feature.

Assumption 6 can be made for systems where the features depend on each other like "building blocks". This kind of dependency information can for example be drawn from some CAD models following the Standard for the Exchange of Product model data (STEP), ISO-10303 [37, 47].

Assumptions 4–6 hold for the sample system. To remove the pipe, the casing must already have been removed. In this case, the assembled modes of the feature variables are *"fitted"* and the disassembled modes are *"removed"*. If Assumptions 4–6 are true, finding a necessary sequence of actions to satisfy the preconditions of any other action can be reduced to a trivial problem. This is described in more detail in Section 3.6.4.

3.4.3 Assumptions of the Probabilistic Model

Assumption 7 (nsDBN for troubleshooting)**.** A probabilistic model that is an nsDBN for troubleshooting as described in Section 2.2.3 can correctly model the dynamics of the system.

Assumption 8 (Persistent components)**.** The mode of a component in one time slice is dependent on its mode in the previous time slice and its mode may only change due to an intervention, i.e. a repair or the operation of the system.

Assumption 8 is valid for systems where the components do not break down or self-heal spontaneously unless the system is operated. This means that all components can be modeled with persistent variables.

Assumption 9 (Non-persistent observations)**.** Observations are only dependent on the state of the components or other observations

Assumption 9 means that all observation variables can be modeled with non-persistent variables.

Assumption 10 (Persistence during Operation)**.** Operation does not affect the mode of persistent variables, i.e. for each persistent variable X,

$$P(x^t|x^{t-1}, operate(\tau)) = \begin{cases} 1 & \text{if } x^t = x^{t-1}, \\ 0 & \text{otherwise.} \end{cases}$$

Assumption 10 is a feasible approximation when Assumptions 8 and 9 hold and the probability of component breakdowns is insignificant unless the duration of operation is very long, e.g., when the system is operated for only a couple of minutes during troubleshooting and the mean time between failures is in the order of months.

Assumption 11 (Function Control)**.** Let $\mathbf{O}_{fc} \subseteq \mathbf{O}$ be observation variables where the outcome space $\Omega_{\mathbf{O}_{fc}}$ can be separated into two disjoint sets Ω_{NF} and Ω_F such that $P(\mathbf{C} = \mathbf{c}|\mathbf{O}_{fc} = \mathbf{o}) = 1$ if $\mathbf{o} \in \Omega_{NF}$ and $\mathbf{c} \in \mathcal{C}_g$ and $P(\mathbf{C} = \mathbf{c}|\mathbf{O}_{fc} = \mathbf{o}) = 0$ if $\mathbf{o} \in \Omega_F$ and $\mathbf{c} \in \mathcal{C}_g$. There exists a sequence of actions that can be performed such that the observation variables $\mathbf{O}_{fc}$ are observed.

Assumption 11 is valid for systems where perfect fault detection is possible, i.e. there is some test that can distinguish between the cases when some component is faulty and no component is faulty.

3.5 Diagnoser

In Figure 1.2 the Diagnoser computes the probabilities of the possible diagnoses and action outcomes. In the current framework, this corresponds to computing the probability

$$P(\mathbf{c}^t|\mathbf{e}^{1:t}, M_P) \tag{3.9}$$

for each $\mathbf{c} \in \Omega_\mathbf{C}$ and computing the probabilities of action outcomes

$$P(\mathbf{e}_a^{t+1:t+n_a}|\mathbf{e}^{1:t}, a, M_P). \tag{3.10}$$

for each action a and action outcome $\mathbf{e}_a^{t+1:t+n_a} \in \Omega_{\mathbf{E}_a^{t+1:t+n_a}}$.

The probability distribution over possible diagnoses given the current events is called the *belief state* as it represents our belief of which components are faulty.

Definition 3.4 (Belief state). The belief state for a troubleshooting problem $I = \langle\langle \mathbf{C}, \mathbf{O}, \mathbf{F}, \mathcal{A}, M_P\rangle, \mathbf{e}^{1:t}, \mathbf{f}^0, \mathcal{F}_g, \mathcal{C}_g\rangle$ is a function $b^t : \Omega_\mathbf{C} \mapsto [0,1]$:

$$b^t(\mathbf{c}) = P(\mathbf{c}^t | \mathbf{e}^{1:t}, M_P). \tag{3.11}$$

□

3.5.1 Computing the Probabilities

Let e^t be an event that can be generated from the effect ϵ^t at time t. Then the probability of having e^t given that ϵ^t occurs at time t and each $\mathbf{c}^t \in \Omega_\mathbf{C}$ and all previous events $\mathbf{e}^{1:t-1}$ is:

$$P(e^t | \mathbf{c}^t, \mathbf{e}^{1:t-1}, \epsilon^t M_P). \tag{3.12}$$

If we know the transition probabilities,

$$P(\mathbf{c}^{t+1} | \bar{\mathbf{c}}^t, \mathbf{e}^{1:t+1}, M_P) \tag{3.13}$$

for all $\mathbf{c}, \bar{\mathbf{c}} \in \Omega_\mathbf{C}$, then when an event e^{t+1} is generated from an effect ϵ^{t+1}, the next belief state b^{t+1} can be can be computed from (3.12), (3.13) and the previous belief state b^t as following:

$$\begin{aligned}
b^{t+1}(\mathbf{c}) &= P(\mathbf{c}^{t+1} | \mathbf{e}^{1:t+1}, M_P) \\
&= \sum_{\bar{\mathbf{c}} \in \Omega_\mathbf{C}} P(\mathbf{c}^{t+1} | \bar{\mathbf{c}}^t, \mathbf{e}^{1:t+1}, M_P) P(\bar{\mathbf{c}}^t | \mathbf{e}^{1:t+1}, M_P) \\
&= \sum_{\bar{\mathbf{c}} \in \Omega_\mathbf{C}} P(\mathbf{c}^{t+1} | \bar{\mathbf{c}}^t, \mathbf{e}^{1:t+1}, M_P) \frac{P(e^{t+1} | \bar{\mathbf{c}}^t, \mathbf{e}^{1:t}, \epsilon^{t+1}, M_P) P(\bar{\mathbf{c}}^t | \mathbf{e}^{1:t}, M_P)}{\sum_{\tilde{\mathbf{c}} \in \Omega_\mathbf{C}} P(e^{t+1} | \tilde{\mathbf{c}}^t, \mathbf{e}^{1:t}, \epsilon^{t+1}, M_P) P(\tilde{\mathbf{c}}^t | \mathbf{e}^{1:t}, M_P)} \\
&= \sum_{\bar{\mathbf{c}} \in \Omega_\mathbf{C}} P(\mathbf{c}^{t+1} | \bar{\mathbf{c}}^t, \mathbf{e}^{1:t+1}, M_P) \frac{P(e^{t+1} | \bar{\mathbf{c}}^t, \mathbf{e}^{1:t}, \epsilon^{t+1}, M_P) b^t(\bar{\mathbf{c}})}{\sum_{\tilde{\mathbf{c}} \in \Omega_\mathbf{C}} P(e^{t+1} | \tilde{\mathbf{c}}^t, \mathbf{e}^{1:t}, \epsilon^{t+1}, M_P) b^t(\tilde{\mathbf{c}})}
\end{aligned} \tag{3.14}$$

Equation (3.14) is the belief state update after event e^{t+1}.

Let a be an action that is performed at time $t+1$ and let $\boldsymbol{\epsilon}_a^{t+1:t+n}$ be the effects of that action. Further, let $\mathbf{e}_a^{t+1:t+n}$ be a sequence of events that can be generated from $\boldsymbol{\epsilon}_a^{t+1:t+n}$, i.e. a possible outcome of a. If we know (3.12) for each effect of a and we know the belief state b^t, then the probabilities of action outcomes (3.10) can be computed as follows. Using standard probability laws we get

$$\begin{aligned}
P(\mathbf{e}_a^{t+1:t+n} | \mathbf{e}^{1:t}, a, M_P) &= \prod_{i=1}^{n} P(e^{t+i} | \mathbf{e}^{1:t+i-1}, \epsilon_a^{t+i}, M_P) \\
&= \prod_{i=1}^{n} \sum_{\mathbf{c} \in \Omega_\mathbf{C}} P(e^{t+i} | \mathbf{c}^{t+i}, \mathbf{e}^{1:t+i-1}, \epsilon_a^{t+i}, M_P) P(\mathbf{c}^{t+i} | \mathbf{e}^{1:t+i-1}, M_P).
\end{aligned}$$

Because all components are persistent and using Definition 2.8,

$$P(\mathbf{c}^{t+1}|\mathbf{e}^{1:t}, M_P) = P(\mathbf{c}^t|\mathbf{e}^{1:t}, M_P) = b^t(\mathbf{c}),$$

therefore,

$$P(\mathbf{e}_a^{t+1:t+n}|\mathbf{e}^{1:t}, a, M_P) = \prod_{i=1}^{n} \sum_{\mathbf{c}\in\Omega_\mathbf{C}} P(e^{t+i}|\mathbf{c}^{t+i}, \mathbf{e}^{1:t+i-1}, e_a^{t+i}, M_P) b^{t+i-1}(\mathbf{c}) \tag{3.15}$$

where b^{t+i-1} is computed from b^{t+i-2} using (3.14).

3.5.2 Static Representation of the nsDBN for Troubleshooting

Let the probabilistic dependency model M_P be an nsDBN B_{ns} where $B_{ns}(\mathbf{e}^{1:t})$ is the resulting BN from the events $\mathbf{e}^{1:t}$. When computing (3.14), finding $P(e^{t+1}|\mathbf{c}^{t+1}, \mathbf{e}^{1:t}, B_{ns}(\mathbf{e}^{1:t+1}))$ is problematic when e^{t+1} is an observation event since the observed variable may depend on component variables earlier than $t+1$. In [58] it is proposed to use a smaller static BN $\hat{B}^t$ which is equivalent to the nsDBN at time t for queries of the same type as (3.12), i.e.:

$$P(e^t|\mathbf{c}^t, \mathbf{e}^{1:t-1}, B_{ns}(\mathbf{e}^{1:t})) = P(e^t|\mathbf{c}^t, \hat{B}^t) \tag{3.16}$$

The initial BN $\hat{B}^0$ is the same as the initial nsDBN $B_{ns}(\emptyset)$. As events occur, the structure of the static BN is updated. After a repair event $C_i^t := NF$, $\hat{B}^t$ is a copy of $\hat{B}^{t-1}$ where all outgoing non-instant edges from C_i are removed. After an operation event $\omega^t(\tau)$ all non-instant edges are restored, i.e. $\hat{B}^t = \hat{B}^0$. After an observation event no change is made to the BN.

In [56] it is proven that (3.16) holds if the structure of $B_{ns}(\emptyset)$ belongs to a certain family of structures $\mathcal{F}^*$ and the events in $\mathbf{e}^{1:t}$ are such that there is at least one operation event between two repair events. However, the second condition is too prohibitive for the purposes of this thesis since we may want to repair multiple components if we are uncertain of which component is faulty. Therefore a different static representation of the nsDBNs for troubleshooting is proposed in this thesis.

A More Efficient Representation

Let t_ω denote the time for the last operation event. A query in an nsDBN, that is conditioned on all persistent variables in the current time slice t and those in time slice t_ω, d-separate all variables in time slices t and t_ω from the variables in all other time slices t' where $t' < t$ and $t' \neq t_\omega$.

If a copy of the persistent variables in time slice t_ω are kept in every time slice of the nsDBN, the nsDBN will only be dependent on the current time slice. This is used to define the static representation of an nsDBN.

Definition 3.5 (Static Representation of an nsDBN)**.** Let

$$B_{ns} = \langle \mathbf{X}_p, \mathbf{X}_{np}, \mathbf{E}_i, \mathbf{E}_{ni}, \Theta^0, \Theta^\omega \rangle$$

be an nsDBN where $\mathbf{X}_p = (X_{p,1}, \ldots, X_{p,n})$ and $\mathbf{X}_{np} = (X_{np,1}, \ldots, X_{np,m})$. The *static representation* of B_{ns} is a BN

$$\hat{B} = \langle \mathbf{X}, \mathbf{E}, \Theta \rangle$$

where:

- the variables $\mathbf{X} = \mathbf{X}_p \cup \bar{\mathbf{X}}_p \cup \mathbf{X}_{np}$, where $\bar{\mathbf{X}}_p = (\bar{X}_{p,1}, \ldots, \bar{X}_{p,n})$ represents the variables $\mathbf{X}_p$ at the time of the last operation event,
- for every *instant* edge $(X_{p,i}, X_{np,j}) \in \mathbf{E}_i$ there is a corresponding edge in $(X_{p,i}, X_{np,j}) \in \mathbf{E}$,
- for every *non-instant* edge $(X_{p,i}, X_{np,j}) \in \mathbf{E}_{ni}$ there is a corresponding edge in $(\bar{X}_{p,i}, X_{np,j}) \in \mathbf{E}$,
- for every directed path in B_{ns} from a *persistent* variable $X_{p,i}$ to a *non-persistent* variable $X_{np,j}$ passing through at least one other *non-persistent* variable such that the outgoing edge from $X_{p,i}$ is *non-instant*, there is an edge $(\bar{X}_{p,i}, X_{np,j}) \in \mathbf{E}$,
- for every directed path in B_{ns} from a *persistent* variable $X_{p,i}$ to a *non-persistent* variable $X_{np,j}$ passing through at least one other *non-persistent* variable such that the outgoing edge from $X_{p,i}$ is *instant*, there is an edge $(X_{p,i}, X_{np,j}) \in \mathbf{E}$, and
- the parameters Θ specify the conditional probabilities $P(X_{np}|\mathbf{X}_p, \bar{\mathbf{X}}_p)$ for each non-persistent variable $X_{np} \in \mathbf{X}_{np}$ of $\hat{B}$ given its parents in $\mathbf{X}_p$ and $\bar{\mathbf{X}}_p$. The parameters do not specify any conditional probabilities for the persistent variable because these will never be used.

The parameters in Θ are created as follows: Let e^1 be a "dummy" observation event at time 1 such that $B_{ns}((e^1))$ has made a single nominal transition. Let $X_{np} \in \mathbf{X}_{np}$ be a non-persistent variable in $\hat{B}$ and let $\mathbf{X}'_p \subseteq \mathbf{X}_p$ and $\bar{\mathbf{X}}'_p \subseteq \bar{\mathbf{X}}_p$ be its parents in $\hat{B}$. Further, let X^1_{np} and $\mathbf{X}'^1_p$ be the corresponding variables to X_{np} and $\mathbf{X}'_p$ in time slice 1 of $B_{ns}((e^1))$ and let $\bar{\mathbf{X}}'^0_p$ be the corresponding variables to $\bar{\mathbf{X}}'_p$ in time slice 0 of $B_{ns}((e^1))$. Then

$$P(X_{np}|\mathbf{X}'_p, \bar{\mathbf{X}}'_p, \hat{B}) = P(X^1_{np}|\mathbf{X}'^1_p, \bar{\mathbf{X}}'^0_p, B_{ns}((e^1))). \tag{3.17}$$

□

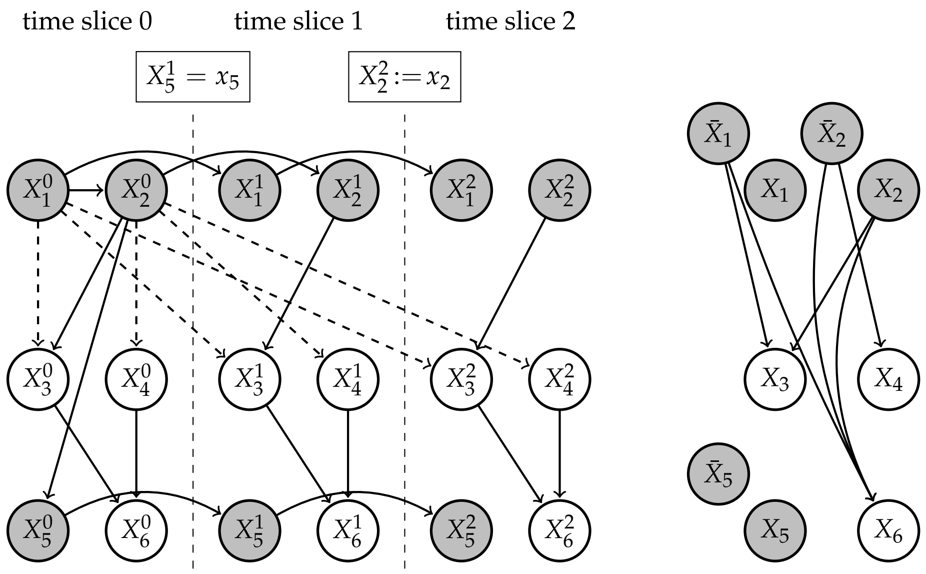


Figure 3.4: The first three time slices of the nsDBN in Example 2.5 (left) and its static representation (right).

Note that $P(X_{np}^1 | \mathbf{X'}_p^1, \bar{\mathbf{X}}'^0_p)$ can be computed using for example the Variable Elimination algorithm described in Section 2.2.4. Also, note that a BN $\hat{B}$ defined according to Definition 3.5 will be a two layer BN.

Figure 3.4 shows the first three time slices of the nsDBN in Example 2.5 and its corresponding static representation. In this example, the parents of the variable X_6^0 are non-persistent. Therefore, we will replace the paths $\{(X_1^0, X_3^0), (X_3^0, X_6^0)\}$, $\{(X_2^0, X_3^0), (X_3^0, X_6^0)\}$ and $\{(X_2^0, X_4^0), (X_4^0, X_6^0)\}$ with the edges $(\bar{X}_1, X_6)$, (X_2, X_6), and $(\bar{X}_2, X_6)$. The conditional probabilities for this variable are obtained by marginalizing away X_3 and X_4:

$$P(X_6{=}x_6 | X_2{=}x_2, \bar{X}_1{=}\bar{x}_1, \bar{X}_2{=}\bar{x}_2) = P(X_6^1{=}x_6 | X_2^1{=}x_2, X_1^0{=}\bar{x}_1, X_2^0{=}\bar{x}_2)$$
$$\sum_{x_3 \in \Omega_{X_3}} \sum_{x_4 \in \Omega_{X_4}} P(X_6^1{=}x_6 | X_3^1{=}x_3, X_4^1{=}x_4) P(X_3^1{=}x_3 | X_1^0{=}\bar{x}_1, X_2^1{=}x_2) P(X_4^1{=}x_4 | X_2^0{=}\bar{x}_2).$$

When using Definition 3.5 as a definition for the static representation of the nsDBN, we can state a theorem similar to (3.16):

Theorem 3.1. Let $\hat{B}$ be the static representation of an nsDBN B_{ns} defined according to Definition 3.5, let $\mathbf{e}^{1:t-1}$ be an arbitrary sequence of events, and let e^t be the event $X^t = x$. Then the two networks $\hat{B}$ and $B_{ns}(\mathbf{e}^{1:t})$ are equivalent for the query of the probability that X has the value x at time t given $\mathbf{e}^{1:t-1}$, i.e.

$$P(X^t = x|\mathbf{X}_p^t = \mathbf{x}, \mathbf{X}_p^{t_\omega} = \bar{\mathbf{x}}, \mathbf{e}^{1:t-1}, B_{ns}(\mathbf{e}^{1:t})) = P(X = x|\mathbf{X}_p = \mathbf{x}, \bar{\mathbf{X}}_p = \bar{\mathbf{x}}, \hat{B}). \tag{3.18}$$

Proof. In the case that e^t is the observation of a persistent variable the equivalence is trivial since $X^t \in \mathbf{X}_p^t$.

Assume now that X^t is non-persistent. We have evidence on all persistent variables in time slices t and t_ω and all paths from X^t to any variable in another time slice is either serial or diverging at a persistent variable in time slice t or t_ω. Therefore, according to Definition 2.2, in $B_{ns}(\mathbf{e}^{1:t})$, the variables in $\mathbf{X}_p^t \cup \mathbf{X}_p^{t_\omega}$ d-separates X^t from all variables in all time slices except t. (see Definition 2.2). There can be no evidence on any other non-persistent variable in time slice t since the nsDBN has one time slice for each event. Therefore

$$P(X^t = x|\mathbf{X}_p^t = \mathbf{x}, \mathbf{X}_p^{t_\omega} = \bar{\mathbf{x}}, \mathbf{e}^{1:t-1}, B_{ns}(\mathbf{e}^{1:t})) = P(X^t = x|\mathbf{X}_p^t = \mathbf{x}, \mathbf{X}_p^{t_\omega} = \bar{\mathbf{x}}, B_{ns}(\mathbf{e}^{1:t})). \tag{3.19}$$

The conditional probabilities of all non-persistent variables are the same in all time slices, therefore

$$P(X^t = x|\mathbf{X}_p^t = \mathbf{x}, \mathbf{X}_p^{t_\omega} = \bar{\mathbf{x}}, B_{ns}(\mathbf{e}^{1:t})) = P(X^1 = x|\mathbf{X}_p^1 = \mathbf{x}, \mathbf{X}_p^0 = \bar{\mathbf{x}}, B_{ns}((e^1))) \tag{3.20}$$

where e^1 is the "dummy event" described in Definition 3.5. Using (3.17) in Definition 3.5 and (3.20), we get

$$P(X^t = x|\mathbf{X}_p^t = \mathbf{x}, \mathbf{X}_p^{t_\omega} = \bar{\mathbf{x}}, B_{ns}(\mathbf{e}^{1:t})) = P(X = x|\mathbf{X}_p = \mathbf{x}, \bar{\mathbf{X}}_p = \bar{\mathbf{x}}, \hat{B}), \tag{3.21}$$

and by applying (3.19) to (3.21), we get the final result

$$P(X^t = x|\mathbf{X}_p^t = \mathbf{x}, \mathbf{X}_p^{t_\omega} = \bar{\mathbf{x}}, \mathbf{e}^{1:t-1}, B_{ns}(\mathbf{e}^{1:t})) = P(X = x|\mathbf{X}_p = \mathbf{x}, \bar{\mathbf{X}}_p = \bar{\mathbf{x}}, \hat{B}).$$

□

This is a stronger result than (3.16) in the way that $\mathbf{e}^{1:t}$ may be an arbitrary sequence of events and that $\hat{B}$ also is stationary, but is weaker in that we also have to condition on the persistent variables at time t_ω. However, if we keep track only of the probability distribution over the persistent variables at time t_ω and the repair events $\mathbf{r}^t$ that has occurred between time t_ω and time t, we can find rules to compute (3.9) and (3.10).

3.5.3 Computing the Probabilities using the Static Representation

Definition 3.6 (Belief state after the last operation event)**.** The *belief state after the last operation event* is a function $b_\omega : \Omega_\mathbf{C} \mapsto [0,1]$:

$$b_\omega^t(\mathbf{c}) = P(\mathbf{C}^{t_\omega} = \mathbf{c}|\mathbf{e}^{1:t}, B_{ns})$$

where t_ω is the time of the most recent operation event in $\mathbf{e}^{1:t}$. □

This represents our belief of the state that the components had at the time of the last operation event given what we know at time t.

Because of Assumption 3, the values of the components statuses at time t can be determined by knowing $\mathbf{r}^t$ and the component statuses at time t_ω. Let $\gamma(\mathbf{r},\mathbf{c}) : \Omega_\mathbf{E} \times \Omega_\mathbf{C} \mapsto \Omega_\mathbf{C}$ be a function that returns a vector that has the same values as $\mathbf{c}$ for all components except those repaired in $\mathbf{r}$ which have the value *NF*, then

$$P(\mathbf{c}^t|\bar{\mathbf{c}}^{t_\omega}, \mathbf{r}^t, B_{ns}) = P(\mathbf{c}^t|\bar{\mathbf{c}}^{t_\omega}, \mathbf{e}^{1:t}, B_{ns}) = \begin{cases} 1 & \text{if } \gamma(\mathbf{r}^t, \mathbf{c}^{t_\omega}) = \mathbf{c}^t, \\ 0 & \text{otherwise.} \end{cases} \tag{3.22}$$

Given the belief state at last operation event b_ω^t and the recent repair events $\mathbf{r}^t$, the belief state b^t can be obtained using (3.22) as

$$\begin{aligned} b^t(\mathbf{c}) &= P(\mathbf{c}^t|\mathbf{e}^{1:t}, B_{ns}) \\ &= \sum_{\bar{\mathbf{c}} \in \Omega_\mathbf{C}} P(\mathbf{c}^t|\bar{\mathbf{c}}^{t_\omega}, \mathbf{e}^{1:t}, B_{ns}) P(\bar{\mathbf{c}}^{t_\omega}|\mathbf{e}^{1:t}, B_{ns}) \\ &= \sum_{\bar{\mathbf{c}} \in \Omega_\mathbf{C}} P(\mathbf{c}^t|\bar{\mathbf{c}}^{t_\omega}, \mathbf{r}^t, B_{ns}) b_\omega^t(\bar{\mathbf{c}}). \end{aligned} \tag{3.23}$$

Corollary 3.1 (Probability of an event)**.** Let e^t be an event that is generated by the effect ϵ^t. Given that b_ω^{t-1} and $\mathbf{r}^{t-1}$ are known then if e^t is an observation event $X^t = x$

$$P(e^t|\mathbf{e}^{1:t-1}, \epsilon^t, B_{ns}) = \sum_{\mathbf{c} \in \Omega_\mathbf{C}} b_\omega^{t-1}(\mathbf{c}) P(X = x|\gamma(\mathbf{r}^{t-1}, \mathbf{c}), \mathbf{c}, \hat{B}), \tag{3.24}$$

otherwise

$$P(e^t|\mathbf{e}^{1:t-1}, \epsilon^t, B_{ns}) = 1. \tag{3.25}$$

Proof. First, we will consider the case where e^t is an observation event $X^t = x$. Identify that

$$\begin{aligned} &P(e^t|\mathbf{e}^{1:t-1}, \epsilon^t, B_{ns}) = P(X^t = x|\mathbf{e}^{1:t-1}, B_{ns}(\mathbf{e}^{1:t})) \\ &\quad = \sum_{\mathbf{c} \in \Omega_\mathbf{C}} P(\mathbf{C}^{t_\omega} = \mathbf{c}|\mathbf{e}^{1:t-1}, B_{ns}(\mathbf{e}^{1:t})) P(X^t = x|\mathbf{C}^{t_\omega} = \mathbf{c}, \mathbf{e}^{1:t-1}, B_{ns}(\mathbf{e}^{1:t})) \end{aligned} \tag{3.26}$$

where, as before, $B_{ns}(\mathbf{e}^{1:t})$ is the BN obtained by applying the events $\mathbf{e}^{1:t}$ on the nsDBN B_{ns}. Note that since e^t is not an operation event, the time t_ω refers to the same time as $(t-1)_\omega$. By applying Definition 3.6 on the result of (3.26) we get

$$P(e^t|\mathbf{e}^{1:t-1}, \epsilon^t, B_{ns}) = \sum_{\mathbf{c}\in\Omega_\mathbf{C}} b_\omega^{t-1}(\mathbf{c}) P(X^t = x|\mathbf{C}^{t_\omega} = \mathbf{c}, \mathbf{e}^{1:t-1}, B_{ns}(\mathbf{e}^{1:t})). \tag{3.27}$$

Identify that

$$\begin{aligned} &P(X^t = x|\mathbf{C}^{t_\omega} = \mathbf{c}, \mathbf{e}^{1:t-1}, B_{ns}(\mathbf{e}^{1:t})) \\ &\quad = \sum_{\bar{\mathbf{c}}\in\Omega_\mathbf{C}} \Big(P(\mathbf{C}^t = \bar{\mathbf{c}}|\mathbf{C}^{t_\omega} = \mathbf{c}, \mathbf{e}^{1:t-1}, B_{ns}(\mathbf{e}^{1:t})) \\ &\qquad\qquad P(X^t = x|\mathbf{C}^t = \bar{\mathbf{c}}, \mathbf{C}^{t_\omega} = \mathbf{c}, \mathbf{e}^{1:t-1}, B_{ns}(\mathbf{e}^{1:t}))\Big). \end{aligned} \tag{3.28}$$

Since $\mathbf{e}^t$ is not a repair event then $\mathbf{r}^t = \mathbf{r}^{t-1}$ and (3.22) can be applied such that

$$\begin{aligned} P(\mathbf{C}^t = \bar{\mathbf{c}}|\mathbf{C}^{t_\omega} = \mathbf{c}, \mathbf{e}^{1:t-1}, B_{ns}(\mathbf{e}^{1:t})) &= P(\mathbf{C}^{t-1} = \bar{\mathbf{c}}|\mathbf{C}^{t_\omega} = \mathbf{c}, \mathbf{e}^{1:t-1}, B_{ns}(\mathbf{e}^{1:t})) \\ &= \begin{cases} 1 & \text{if } \gamma(\mathbf{r}^{t-1}, \mathbf{c}) = \bar{\mathbf{c}}, \\ 0 & \text{otherwise.} \end{cases} \end{aligned} \tag{3.29}$$

By using (3.29) on (3.28) we get that

$$P(X^t = x|\mathbf{C}^{t_\omega} = \mathbf{c}, \mathbf{e}^{1:t-1}, B_{ns}(\mathbf{e}^{1:t})) = P(X^t = x|\mathbf{C}^t = \gamma(\mathbf{r}^{t-1}, \mathbf{c}), \mathbf{C}^{t_\omega} = \mathbf{c}, \mathbf{e}^{1:t-1}, B_{ns}(\mathbf{e}^{1:t})) \tag{3.30}$$

By applying Theorem 3.1 on the result of (3.30) and inserting this into (3.27), we get the final result:

$$P(e^t|\mathbf{e}^{1:t-1}, \epsilon^t, B_{ns}) = \sum_{\mathbf{c}\in\Omega_\mathbf{C}} b_\omega^{t-1}(\mathbf{c}) P(X = x|\gamma(\mathbf{r}^{t-1}, \mathbf{c}), \mathbf{c}, \hat{B}). \tag{3.31}$$

When e^{t+1} is some other type of event, then the effect ϵ^{t+1} that generated it cannot generate any other event. Therefore, the probability of having e^{t+1} given ϵ^{t+1} must be one. □

Updating b_ω After Events

As events occur, the belief state at the last operation event is updated and b_ω^{t+1} is computed from b_ω^t, $\mathbf{r}^t$, and the last event e^{t+1}.

Corollary 3.2 (Update after observation)**.** Let e^{t+1} be an observation event $X^{t+1}=x$. Given that b^t_ω and $\mathbf{r}^t$ are known then

$$b^{t+1}_\omega(\mathbf{c}) = \frac{b^t_\omega(\mathbf{c})P(X=x|\gamma(\mathbf{r}^t,\mathbf{c}),\mathbf{c},\hat{B})}{\sum\limits_{\bar{\mathbf{c}}\in\Omega_{\mathbf{C}}} b^t_\omega(\bar{\mathbf{c}})P(X=x|\gamma(\mathbf{r}^t,\bar{\mathbf{c}}),\bar{\mathbf{c}},\hat{B})} \tag{3.32}$$

Proof. Using, Definition 3.6, identify that

$$\begin{aligned} b^{t+1}_\omega(\mathbf{c}) &= P(\mathbf{C}^{t_\omega}=\mathbf{c}|\mathbf{e}^{1:t},X^{t+1}=x,B_{ns}) \\ &= \frac{P(X^{t+1}=x|\mathbf{C}^{t_\omega}=\mathbf{c},\mathbf{e}^{1:t},B_{ns})P(\mathbf{C}^{t_\omega}=\mathbf{c}|\mathbf{e}^{1:t},B_{ns})}{P(X^{t+1}=x|\mathbf{e}^{1:t},B_{ns})}. \end{aligned} \tag{3.33}$$

Further, identify that

$$\begin{aligned} &P(X^{t+1}=x|\mathbf{C}^{t_\omega}=\mathbf{c},\mathbf{e}^{1:t},B_{ns}) \\ &\quad = \sum_{\bar{\mathbf{c}}\in\Omega_{\mathbf{C}}} P(X^{t+1}=x|\mathbf{C}^{t+1}=\bar{\mathbf{c}},\mathbf{C}^{t_\omega}=\mathbf{c},\mathbf{e}^{1:t},B_{ns})P(\mathbf{C}^{t+1}=\bar{\mathbf{c}}|\mathbf{C}^{t_\omega}=\mathbf{c},\mathbf{e}^{1:t},B_{ns}). \end{aligned} \tag{3.34}$$

Since e^{t+1} is not an operation event, the time t_ω refers to the same time as $(t+1)_\omega$. By applying (3.22) and then Theorem 3.1 on (3.34) we get

$$\begin{aligned} P(X^{t+1}=x|\mathbf{C}^{t_\omega}=\mathbf{c},\mathbf{e}^{1:t},B_{ns}) &= P(X^{t+1}=x|\mathbf{C}^{t+1}=\gamma(\mathbf{r}^t,\mathbf{c}),\mathbf{C}^{t_\omega}=\mathbf{c},\mathbf{e}^{1:t},B_{ns}) \\ &= P(X^{t+1}=x|\gamma(\mathbf{r}^t,\mathbf{c}),\mathbf{c},\mathbf{e}^{1:t},\hat{B}). \end{aligned} \tag{3.35}$$

The final result (3.32) is obtained by inserting (3.35) into (3.33) and applying Corollary 3.1 and Definition 3.6. □

Analogously as for Corollary 3.1, when Assumption 3 applies, (3.32) can be simplified into:

$$b^{t+1}_\omega(\mathbf{c}) = \frac{b^t_\omega(\mathbf{c})P(X=x|\gamma(\mathbf{r}^t,\mathbf{c}),\mathbf{c},\hat{B})}{\sum\limits_{\bar{\mathbf{c}}} b^t_\omega(\bar{\mathbf{c}})P(X=x|\gamma(\mathbf{r}^t,\bar{\mathbf{c}}),\bar{\mathbf{c}},\hat{B})} \tag{3.36}$$

If the event at time $t+1$ is a repair event, the belief state after the last operation event does not change because it does not give us any new knowledge of which components were faulty at time t_ω, i.e.

$$\begin{aligned} b^{t+1}_\omega &= b^t_\omega \\ \mathbf{r}^{t+1} &= \mathbf{r}^t \cup e^{t+1}. \end{aligned} \tag{3.37}$$

If the event at time $t+1$ is an operation event, the next belief state after operation becomes equal to the belief state b^{t+1} and the set of recent events is cleared $\mathbf{r}^{t+1} = \emptyset$. Let $P(\mathbf{c}|\bar{\mathbf{c}}, \omega(\tau))$ be the probability that the component statuses are $\mathbf{c}$ after an operation event of duration τ given that they were $\bar{\mathbf{c}}$ before. Then using (3.23)

$$b_\omega^{t+1}(\mathbf{c}) = \sum_{\bar{\mathbf{c}}} P(\mathbf{c}|\bar{\mathbf{c}}, \omega(\tau), B_{ns}) \sum_{\tilde{\mathbf{c}}} P(\bar{\mathbf{c}}|\tilde{\mathbf{c}}, \mathbf{r}^t, B_{ns}) b_\omega^t(\tilde{\mathbf{c}}). \tag{3.38}$$

Because of Assumption 3 and Assumption 10, repairs are perfect and components do not break down during operation. Let $\mathbb{1}_x(y)$ be an indicator function, such that if $x = y$, then $\mathbb{1}_x(y) = 1$ and otherwise, $\mathbb{1}_x(y) = 0$. Then (3.38) can be significantly simplified into:

$$b_\omega^{t+1}(\mathbf{c}) = \sum_{\bar{\mathbf{c}}} \mathbb{1}_{\mathbf{c}}(\gamma(\mathbf{r}^t, \bar{\mathbf{c}})) b_\omega^t(\bar{\mathbf{c}}). \tag{3.39}$$

With the update rules (3.32), (3.37), (3.38), the belief state after operation can be tracked for all events that may occur. Then using (3.23) and (3.24) we can fulfill the task of the Diagnoser.

Example 3.5 (Tracking the Belief State for the Sample System)**.** Consider the sequence of events in the left-most path in Figure 3.3. The events regarding feature variables are ignored and an operation event is also generated for the Test System action. The sequence of events is

$$\mathbf{e}^{1:7} = (O_3^1 = ind., C_4^2 = NF, C_1^3 = fail., C_1^4 := NF, \omega^5(\tau), O_3^6 = ind., C_3^7 := NF).$$

The initial distribution b^0 is computed using the initial time slice of the nsDBN:

$$b^0(\mathbf{c}) = P(\mathbf{c}^0|B_{ns}(\emptyset)) = P(c_1|B_{ns}(\emptyset))P(c_2|B_{ns}(\emptyset))P(c_3|B_{ns}(\emptyset))P(c_4|c_2 B_{ns}(\emptyset)).$$

At $t = 0$, $t_\omega = t$, so therefore $b_\omega^0 = b$. The static representation $\hat{B}$ will be flattened out to a two layer BN. Therefore the CPT for O_3 will be the following:

C_1	C_3	C_4	$P(O_3 = ind.\|C_1, C_2, C_4)$
NF	*NF*	*NF*	0
NF	*NF*	*low*	1
NF	*fail.*	*NF*	1
NF	*fail.*	*low*	1
fail.	*NF*	*NF*	1
fail.	*NF*	*low*	1
fail.	*fail.*	*NF*	1
fail.	*fail.*	*low*	1

Table 3.1: Belief states at time of operation in Example 3.5. Entries in the table where $b^t_\omega(\mathbf{c}) = 0$ are blank.

$\mathbf{r}^t$	$\emptyset$	$\emptyset$	$\emptyset$	$\emptyset$	$(C^4_1 := NF)$	$\emptyset$	$(C^6_3 := NF)$
$\mathbf{c} = (c_1, c_2, c_3, c_4)$	$b^0_\omega(\mathbf{c})$	$b^1_\omega(\mathbf{c})$	$b^2_\omega(\mathbf{c})$	$b^3_\omega(\mathbf{c})$	$b^4_\omega(\mathbf{c})$	$b^5_\omega(\mathbf{c})$	$b^6_\omega(\mathbf{c})$
(NF, NF, NF, NF)	0.994					0.996	
(F, NF, NF, NF)	0.001	0.166	0.199	0.996	0.996		
(NF, F, NF, NF)							
(F, F, NF, NF)							
(NF, NF, F, NF)	0.004	0.666	0.800			0.004	1
(F, NF, F, NF)	$4{\cdot}10^{-6}$	$7{\cdot}10^{-4}$	$8{\cdot}10^{-4}$	0.004	0.004		
(NF, F, F, NF)							
(F, F, F, NF)							
(NF, NF, NF, F)							
(F, NF, NF, F)							
(NF, F, NF, F)	0.001						
(F, F, NF, F)	$1{\cdot}10^{-6}$						
(NF, NF, F, F)							
(F, NF, F, F)							
(NF, F, F, F)	$4{\cdot}10^{-6}$						
(F, F, F, F)	$4{\cdot}10^{-9}$						

The values of $b^t_\omega(\mathbf{c})$ for all $\mathbf{c} = (c_1, c_2, c_3, c_4) \in \Omega_\mathbf{C}$, $t \in [0, 7]$ are shown in Table 3.1. The first three events are observation events so the rule (3.36) is used to update b^t_ω:

$$\begin{aligned}
&b^1_\omega(\mathbf{c}) \propto P(O_3 = ind.|C_1 = c_1, C_3 = c_3, C_4 = c_4, \hat{B}) b^0_\omega(\mathbf{c}) \\
&b^2_\omega(\mathbf{c}) \propto P(C_4 = NF|C_4 = c_4, \hat{B}) b^1_\omega(\mathbf{c}) \\
&b^3_\omega(\mathbf{c}) \propto P(C_1 = fail.|C_1 = c_1, \hat{B}) b^2_\omega(\mathbf{c}).
\end{aligned}$$

The probability of the event outcome, $P(C_3 = fail.|\mathbf{e}^{1:2})$, is obtained during normalization, i.e.

$$P(C_1 = fail.|\mathbf{e}^{1:2}) = \sum_{\mathbf{c} \in \Omega_\mathbf{C}} P(C_1 = fail.|C_1 = c_1, \hat{B}) b^2_\omega(\mathbf{c}) \approx 0.2002.$$

The fourth event is a repair event so the rule (3.37) is used to update b_ω, i.e., no change is made and $C^4_1 := NF$ is added to the list of repairs.

The fifth event is an operation event and now the effect of $C^4_1 := NF$ will be accounted for when b_ω is updated using the rule (3.38):

$$b^5_\omega(\mathbf{c}) = \sum_{\bar{\mathbf{c}} \in \Omega_\mathbf{C}} \mathbb{1}_\mathbf{c}(\gamma(\mathbf{r}^4, \bar{\mathbf{c}})) b^4_\omega(\bar{\mathbf{c}}) = \begin{cases} b^4_\omega(\mathbf{c}) + b^4_\omega((c_1, c_2, c_3, low)) & \text{if } \mathbf{c} = (c_1, c_2, c_3, NF), \\ 0 & \text{if } \mathbf{c} = (c_1, c_2, c_3, low). \end{cases}$$

After the last event, troubleshooting stops because the system is believed to be repaired, i.e. using (3.23):

$$b^6((NF, NF, NF, NF)) = \sum_{\bar{\mathbf{c}} \in \Omega_\mathbf{C}} \mathbb{1}_{(NF,NF,NF,NF)}(\gamma(\mathbf{r}^6, \bar{\mathbf{c}})) b^6_\omega(\bar{\mathbf{c}}) = 1.$$

3.6 Planner

The second component of the troubleshooting framework is the Planner. Its purpose is to recommend actions to the user so that the expected cost of repair (3.6) becomes minimal. This may be done by finding an optimal troubleshooting plan as given by (3.8). However, it is not necessary to explicitly know the entire plan. It is sufficient to know that the next action is part of an optimal plan. The Planner explores a portion of the space of all possible plans that is large enough to give an estimate of the optimal expected cost of repair. The first action in this plan is the decision. While this action is executed by the user, the Planner has time to come up with the next decision. We will formulate the decision problem as a Stochastic Shortest Path Problem (SSPP) and thereby be able to use any solver for SSPP:s to find the plans on which the decisions are based upon.

3.6.1 Modeling the Troubleshooting Problem as a Stochastic Shortest Path Problem

The SSPP as defined in Definition 2.11 is a tuple $\langle \mathcal{S}, \mathcal{A}, p, c, s_0, \mathcal{S}_g \rangle$ where $\mathcal{S}$ is the state space, $\mathcal{A}$ is the set of possible actions, p is the transition probability function, c is the cost function, s_0 is the initial state, and $\mathcal{S}_g$ is the set of goal states.

The transition probability function gives the probability of having a certain action outcome in a certain state. A state $s \in \mathcal{S}$ of the SSPP must contain sufficient information so that the transition probability function can be computed efficiently. Using the static representation described in Section 3.5.2, the probability distribution over component statuses (3.9) and the probabilities of action outcomes (3.10) can be computed from the belief state after the last operation event b_ω and a list of recent repair events $\mathbf{r}$. Therefore it is appropriate that the state contains this information.

The actions have preconditions depending on the values of the feature variables and effects that can affect the values of feature variables. Therefore a state in the SSPP for troubleshooting will also specify the values of all feature variables. A state that contains information of the belief state after the last operation event, the repair events that have occurred since the last operation event, and the current status of the feature variables, is called a *system state*.

Definition 3.7 (System state)**.** Let $I = \langle M, \mathbf{e}^{1:t}, \mathbf{f}^0, \mathcal{F}_g, \mathcal{C}_g \rangle$ be a troubleshooting problem where Assumptions 7–9 hold. Then a *system state* corresponding to the troubleshooting problem I is a tuple $s = \langle b_\omega, \mathbf{r}, \mathbf{f} \rangle$ where b_ω is a belief state after the last operation event before the time t as defined in Definition 3.6, $\mathbf{r}$ is an unordered set of all repair events that have occurred since this operation event, and $\mathbf{f}$ specifies the values of all feature variables given the events that have occurred up to time t. If no operation event has occurred $b_\omega = b^0$ and $\mathbf{r}$ consists of all repair events that have occurred up to time t. □

State Transitions

Let $I_1 = \langle M, \mathbf{e}^{1:t}, \mathbf{f}^0, \mathcal{F}_g, \mathcal{C}_g \rangle$ and $I_2 = \langle M, \mathbf{e}^{1:t}; e, \mathbf{f}^0, \mathcal{F}_g, \mathcal{C}_g \rangle$ be two troubleshooting problems where Assumptions 7–9 hold and let $s_1 = \langle b_{\omega 1}, \mathbf{r}_1, \mathbf{f}_1 \rangle$ and $s_2 = \langle b_{\omega 2}, \mathbf{r}_2, \mathbf{f}_2 \rangle$ be their corresponding system states. If the event e is a feature event $F := f$, s_2 can be computed from s_1 by first letting $\mathbf{f}_2 = \mathbf{f}_1$ and then setting the element in $\mathbf{f}_2$ corresponding to F to f. A feature event will have no effect on the belief state, therefore $b_{\omega 2} = b_{\omega 1}$ and $\mathbf{r}_2 = \mathbf{r}_1$. In the case of any other type of event, $b_{\omega 2}$ and $\mathbf{r}_2$ can be computed from $b_{\omega 1}$ and $\mathbf{r}_1$ in the Diagnoser using the rules described in Section 3.5.3. Only feature events affect the feature variables, therefore in this case $\mathbf{f}_2 = \mathbf{f}_1$. The initial state s_0, corresponding to a troubleshooting problem $I_0 = \langle M, \emptyset, \mathbf{f}^0, \mathcal{F}_g, \mathcal{C}_g \rangle$, is $\langle b_{\omega 0}, \mathbf{r}_0, \mathbf{f}_0 \rangle$ where $b_{\omega 0}(\mathbf{c}) = P(\mathbf{C}^0 = \mathbf{c} | \emptyset, M_P)$ for all $\mathbf{c} \in \Omega_{\mathbf{C}}$ and $\mathbf{r} = \emptyset$.

An action a may have multiple effects which are treated in sequence. Therefore each outcome of an action with k effects is a sequence of events $\mathbf{e} = (e_1, \ldots, e_k)$. Let $s_i = \langle b_{\omega i}, \mathbf{r}_i, \mathbf{f}_i \rangle$ be the state that is reached when the event e_i occurs in the state $s_{i-1} = \langle b_{\omega i-1}, \mathbf{r}_{i-1}, \mathbf{f}_{i-1} \rangle$. Further, let $s' = s_k$ be the system state that is reached from the state $s = s_0$ given $\mathbf{e}$. Then using Corollary 3.1, we can compute the value returned by the transition probability function $p(s', s, a)$ as

$$p(s_k, s_0, a) = \prod_{i=1}^{k} \Big(\sum_{\bar{\mathbf{c}}} b_{\omega i-1}(\bar{\mathbf{c}}) \sum_{\mathbf{c}} P(\mathbf{c} | \bar{\mathbf{c}}, \mathbf{r}_{i-1}) P(e_i | \mathbf{c}, \bar{\mathbf{c}}, \hat{B}) \Big).$$

The successor function $succ(a, s)$ defined in Definition 2.6 gives the set of system states that can be reached with the action a from the system state s with non-zero probability.

If the precondition of an action a is not fulfilled in a state s, $p(s', s, a) = 0$ for all states $s' \neq s$. This means that the action will not affect the system state because it cannot be executed.

Actions

The set of actions for the troubleshooting problem and the SSPP are the same. Because of the preconditions, some actions will have no effect in certain states and they may never be part of any optimal troubleshooting plan. Such actions are said to be not *applicable* in those states.

Definition 3.8 (Applicable Actions)**.** An action a is said to be *applicable* in state s if there exist a state $s' \in \mathcal{S}$ such that $s' \neq s$ and $p(s', s, a) > 0$. For any state s, the set of applicable actions $\mathcal{A}_s \subseteq \mathcal{A}$ consist of all actions that are applicable in s. □

In every state s, only the actions in $\mathcal{A}_s$ need to be considered. Definition 3.8 also excludes actions that are inappropriate because they will lead to the same system state even though they are physically executable, e.g. repairing a component that is already repaired or making an observation where it is already known what the outcome will be.

The action costs in the cost function c are taken directly from the troubleshooting model, and are independent of the state.

Goal States

The set of absorbing goal states of the SSPP is:

$$\mathcal{S}_g = \{\langle b_\omega, \mathbf{r}, \mathbf{f}\rangle : \mathbf{f} \in \mathcal{F}_g, \sum_{\mathbf{c}\in\mathcal{C}_g} b(\mathbf{c}) = 1\}$$

where b is computed from b_ω and $\mathbf{r}$ using (3.23), and $\mathcal{F}_g \subseteq \Omega_\mathbf{F}$ and $\mathcal{C}_g \subseteq \Omega_\mathbf{C}$ specify the permitted combinations of modes for feature and component variables when troubleshooting is complete. We will assume that $\mathcal{F}_g$ is a singleton $\{\mathbf{f}_g\}$ where $\mathbf{f}_g$ is such that all feature variables are in the mode assembled and following Assumption 1, $\mathcal{C}_g = \{\mathbf{c}_g\}$ where $\mathbf{c}_g$ is such that all component variables are in a non-faulty mode.

3.6.2 Solving the SSPP

From the Planner's point of view, all it has to do is to find a partial policy π for an SSPP and be able to return the first action of that policy $\pi(s_0)$ anytime. The initial state s_0 is given and the functions p, *succ*, and testing for membership in $\mathcal{S}_g$ are implemented by the Diagnoser. Therefore the Planner can be implemented by any algorithm for solving SSPP:s that can return an approximate solution anytime.

A policy π for the SSPP for a troubleshooting problem $I = \langle M, \mathbf{e}^{1:t}, \mathbf{f}^0, \mathcal{F}_g, \mathcal{C}_g\rangle$ that has finite cost corresponds to a troubleshooting plan π_I that is a solution to I. For every sequence of events $\mathbf{e}$ leading from the initial state to a system state s, $\pi_I(\mathbf{e}^{1:t}; \mathbf{e}) = \pi(s)$.

Theorem 3.2. Let $I = \langle M, \mathbf{e}^{1:t}, \mathbf{f}^0, \mathcal{F}_g, \mathcal{C}_g\rangle$ be a troubleshooting problem where Assumptions 7–9 hold and let $\langle \mathcal{S}, \mathcal{A}, p, c, s_0, \mathcal{S}_g\rangle$ be an SSPP corresponding to the troubleshooting problem I. Further let π^* be an optimal policy for the SSPP and let π_I be the corresponding troubleshooting plan. Then π_I is an optimal troubleshooting plan, i.e. $V_{\pi^*}(s_0) = ECR(\pi_I, \mathbf{e}^{1:t}) = ECR^*(\mathbf{e}^{1:t})$.

Proof. For every sequence of events $\mathbf{e}$ leading from the initial state to a system state s, $\pi^*(s)$ is the same action as $\pi_I(\mathbf{e}^{1:t}; \mathbf{e})$. Therefore, $c(\pi^*(s), s)$ in (2.7) corresponds to $c_{\pi_I(\mathbf{e}^{1:t};\mathbf{e})}$ in (3.7). For every sequence of events $\bar{\mathbf{e}} \in \mathbf{E}_{\pi_I(\mathbf{e}^{1:t};\mathbf{e})}$ that can be generated by the action $\pi_I(\mathbf{e}^{1:t}; \mathbf{e})$ we can generate another system state s' using the rules in Corollary 3.2, (3.37), and (3.38). Using Corollary 3.1 and (3.10) we know that $p(s', s, \pi^*(s))$ in (2.7) corresponds to $P(\bar{\mathbf{e}}|\mathbf{e}^{1:t}, \pi^*(\mathbf{e}^{1:t}), M_P)$ in (3.7) and we can identify that (2.7) and (3.7) are the same for all sequences of events $\mathbf{e}^{1:t}; \mathbf{e}$ and their corresponding system states. □

3.6.3 Search Heuristics for the SSPP for Troubleshooting

Many algorithms for solving SSPP:s gain from using search heuristics. A heuristic is a function $h : \mathcal{S} \mapsto \mathbb{R}^+$ that estimates the expected cost of reaching a goal state from any given state in the state space. Algorithms such as LAO* and RTDP require that the heuristic is an *admissible lower bound* in order to guarantee convergence toward an optimal policy, i.e. they require $h(s) \leq V_{\pi^*}(s)$ for all $s \in \mathcal{S}$. An admissible lower bound can be used by the algorithms to prove that certain parts of the search space cannot be part of an optimal policy and can thereby safely be ignored.

Algorithms such as FRTDP [76], BRTDP [46], and VPI-RTDP [67] are helped by also having a heuristic that can give an upper bound of the optimal expected cost, i.e. $h(s) \geq V_{\pi^*}(s)$ for all $s \in \mathcal{S}$. Such a heuristic said to be an *admissible upper bound*.

Apart from that the heuristics are admissible, it is also important that they can be efficiently computed. Typically we want the heuristic to be computable in polynomial time. In this section will present some polynomial time search heuristics that are useful for solving the troubleshooting problem when it is formulated as an SSPP.

Lower Bound Heuristics

A common way to create lower bound heuristics is to solve a simplified version of the problem. In Bonet [8] a heuristic for SSPP:s, called the h_{min}-heuristic, is created through a relaxation where it is assumed that we can choose action outcomes freely. Then the problem becomes an ordinary shortest path problem that can be solved optimally with algorithms such as A* [32] or Dijkstras algorithm [23]. However, this relaxed problem cannot in general be solved in polynomial time since the size of the search graph for this shortest path problem is exponential in the number of possible actions. If we have a troubleshooting problem where Assumption 11 holds, then for any state where there is a non-zero probability that no component is faulty, the heuristic would at most return the cost of making a function control that has a positive outcome.

When the SSPP is a belief-MDP, we can create a heuristic where the relaxation is to create a corresponding SSPP under the assumption of full observability and solve that simpler SSPP instead [78]. The cost of solving the relaxed problem for each underlying state is weighted with the probability of that state in the belief state. When applied to the troubleshooting problem, this is equivalent to assuming the existence of a single observing action of zero cost that completely determines the values of all component variables. For each possible outcome of this observing action, we can quickly calculate a short sequential plan repairing all faulty components with optimal cost. The probability of each outcome of this observing action is the probability of each diagnosis.

Let $s = \langle b_\omega, \mathbf{r}, \mathbf{f} \rangle$ and let b be the belief state computed from b_ω using (3.23). Further, let $c(\mathbf{c}, \mathbf{f})$ be the minimal cost of repairing the faulty components in $\mathbf{c}$ and setting the feature values to some $\mathbf{f}_g \in \mathcal{F}_g$ given the values of the feature variables $\mathbf{f}$. Then the full observability heuristic h_{fo} is defined as:

$$h_{fo}(s) = \sum_{\mathbf{c} \in \Omega_\mathbf{C}} b(\mathbf{c}) c(\mathbf{c}, \mathbf{f}). \tag{3.40}$$

Another way to create a search heuristic is to measure the level of uncertainty in the state. In all goal states, we have full certainty since a goal state is a system state where the probability that all components are non-faulty is 1. The uncertainty can be measured using the entropy:

$$H(s) = - \sum_{\mathbf{c} \in \Omega_\mathbf{C}} b(\mathbf{c}) \log_2 b(\mathbf{c}). \tag{3.41}$$

where $H(s) = 0$ means that we have full certainty of the current diagnosis in s.

An observing event with n possible outcomes can at most reduce the entropy by $\log_2 n$ [30] and a repair event of a component with n fault modes may at most reduce the entropy by $\log_2(n+1)$. An action that may generate multiple events can reduce the entropy by at most an amount corresponding to the sum of the entropy each individual event may reduce. Let $c_H(a)$ be the minimum cost of reducing the entropy by one through the action a. A heuristic based on entropy h_{ent} can be formed as following:

$$h_{ent}(s) = H(s) \min_{a \in \mathcal{A}} c_H(a). \tag{3.42}$$

The full observability heuristic h_{fo} gives a measure of what must at least be spent repairing faulty components while the entropy heuristic h_{ent} gives a measure of what must at least be spent gaining more information of the true state. In Sun and Weld [79] these two heuristics are combined when the troubleshooting problem is solved using look-ahead search. However, a heuristic $h = h_{fo} + h_{ent}$ would not be an admissible lower bound because the heuristics are not completely independent since repair events also reduce the entropy. For look-ahead search this is not a problem, but for the SSPP for troubleshooting, we require the heuristics to be admissible.

To create an admissible heuristic combining both h_{fo} and h_{ent} we must disregard any entropy that could be removed by the repairs in the calculation of h_{ent}. Let $\hat{H}(\mathbf{c})$ be the amount of entropy that is reduced by repairing the faulty components in **c** in a system state with maximal entropy. Then a combined heuristic h_{comb} can be defined as:

$$h_{comb}(s) = h_{fo}(s) + \max\left(0, H(s) - \sum_{\mathbf{c}\in\Omega_{\mathbf{C}}} b(\mathbf{c})\hat{H}(\mathbf{c})\right) \min_{a\in\mathcal{A}} c_H(a) \qquad (3.43)$$

Theorem 3.3. Let s be any system state in an SSPP for troubleshooting and let π^* be an optimal policy for the SSPP. Then $h_{comb}(s) \leq V_{\pi^*}(s)$.

Proof. In any system state s, the faulty components in **c** must be repaired with the probability $b(s)$. This will cost at least $c(\mathbf{c}, \mathbf{f})$ and reduce the entropy in the state with at most $\hat{H}(\mathbf{c})$. Because the entropy is zero in all goal states, the remaining entropy must be accounted for. This will cost at least $(H(s) - \sum_{\mathbf{c}\in\Omega_{\mathbf{C}}} b(\mathbf{c})\hat{H}(\mathbf{c})) \min_{a\in\mathcal{A}} c_H(a)$. □

This heuristic can be computed in time linear in the size of the belief state. In Section 5.4 we shall see that using this heuristic instead of h_{fo} or h_{ent} improves the performance of the Planner.

Example 3.6. Consider the sample system that is described in Section 3.1 and modeled in Section 3.2. After making the action a_8 and the observation $O_3 =$ *indicating*, a system state $s = \langle b_\omega, \mathbf{r}, \mathbf{f}\rangle$ is reached where $\mathbf{r} = \emptyset$, $\mathbf{f} = [fit, fit]$ and:

$[c_1$	c_2	c_3	$c_4\ ]$	$b(\mathbf{c})$	$c(\mathbf{c}, \mathbf{f})$
[*NF*,	*NF*,	*NF*,	*NF*,]	0	0
[*failure*,	*NF*,	*NF*,	*NF*,]	0.124	200
[*NF*,	*leakage*,	*NF*,	*NF*,]	0	145
[*failure*,	*leakage*,	*NF*,	*NF*,]	0	295
[*NF*,	*NF*,	*failure*,	*NF*,]	0.500	100
[*failure*,	*NF*,	*failure*,	*NF*,]	$5.0 \cdot 10^{-4}$	300
[*NF*,	*leakage*,	*failure*,	*NF*,]	0	245
[*failure*,	*leakage*,	*failure*,	*NF*,]	0	395
[*NF*,	*NF*,	*NF*,	*low*]	0.249	20
[*failure*,	*NF*,	*NF*,	*low*]	$2.5 \cdot 10^{-4}$	220
[*NF*,	*leakage*,	*NF*,	*low*]	$1.2 \cdot 10^{-4}$	165
[*failure*,	*leakage*,	*NF*,	*low*]	$8.0 \cdot 10^{-5}$	315
[*NF*,	*NF*,	*failure*,	*low*]	0.0010	120
[*failure*,	*NF*,	*failure*,	*low*]	$1.0 \cdot 10^{-6}$	320
[*NF*,	*leakage*,	*failure*,	*low*]	$5.0 \cdot 10^{-4}$	265
[*failure*,	*leakage*,	*failure*,	*low*]	$5.0 \cdot 10^{-7}$	415

In this state the h_{min}-heuristic would yield the value 60 corresponding to the repair of C_4 using a_2 followed by an observation of O_3 using a_8 and having the outcome $O_3 =$ *not indicating*. The entropy in this state $H(s) \approx 2.08$. All repair actions and observing actions may reduce the entropy by at most one and the cheapest action cost is 10 and thereby $h_{ent}(s) \approx 17.4$. The full observability heuristic gives a higher value: $h_{fo}(s) \approx 100.9$. After the repairs the expected remaining entropy is approximately 0.65 and thereby $h_{comb}(s) \approx 107.3$.

Upper Bound Heuristics

Heckerman et al. [33] describes a heuristic for troubleshooting using look-ahead search. We will use this heuristic as a starting point for creating a search heuristic that is an admissible upper bound for the troubleshooting problem. Heckerman et al. made the following assumptions: actions have no preconditions, at most one component can be faulty, and on the onset of troubleshooting the probability that some component is faulty is 1. The set of possible actions is restricted to be actions that replace a component, actions that observe the value of a component variable, and a function control action as specified by Assumption 11. An upper bound heuristic is created by transforming the problem into a more difficult problem that is easier to solve. Therefore, it is required that the function control action is performed after each repair action, because then it is possible to compute the optimal expected cost of repair analytically. A troubleshooting plan π_1, where each component in turn is first observed and then if necessary is replaced, is guaranteed to reach a goal state. It is proven that if the components are observed in descending order by the ratio between their probability of being faulty and the cost of observing them, this troubleshooting plan will be optimal for this simplified and restricted case.

Let p_i be the probability that component C_i is faulty in the system state s, let c_i^{rep} be the cost of replacing C_i, let c_i^{obs} be the cost of observing the mode of C_i, and let c^{fc} be the cost of performing the function control. The expected cost of π_1 is

$$V_{\pi_1}(s) = \sum_{i=1}^{|\mathbf{C}|} \left(\left(1 - \sum_{j=1}^{i-1} p_j\right) c_i^{obs} + p_i(c_i^{rep} + c^{fc}) \right). \tag{3.44}$$

The inner sum $1 - \sum_{j=1}^{i-1} p_j$, is the probability that no earlier component C_j, $j < i$, is faulty. This is the probability that C_i is observed because it is assumed that no more than one component can be faulty at the same time. When a component is found to be faulty, that component is replaced and troubleshooting is complete. If C_i cannot be observed by any action, it is instead repaired immediately and a function control is used to verify whether C_i was before the repair or not. Therefore, if C_i cannot be observed by any action, we set c^{rep} and c^{fc} to zero and substitute c_i^{obs} with the cost of repairing it plus doing the function control. A heuristic $h = V_{\pi_1}$ is an admissible upper bound for the troubleshooting

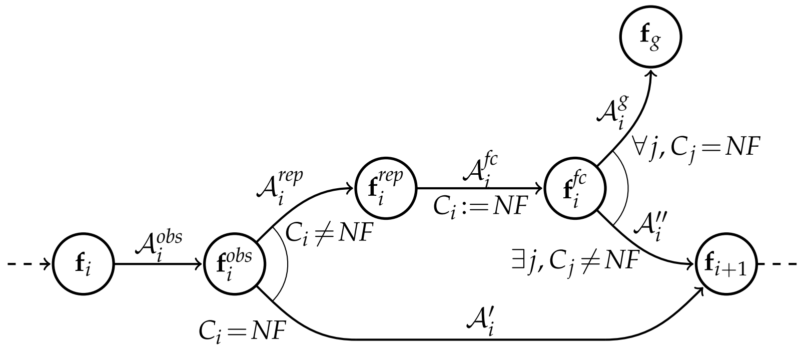


Figure 3.5: A troubleshooting plan for repairing an observable component C_i.

problem specified in Heckerman et al. [33], because a policy with equal or smaller expected cost can always be found if we allow all actions and remove the requirement of performing the function control.

We will extend this heuristic to create an upper bound heuristic for the troubleshooting problem specified in this thesis where actions have preconditions and multiple components can be faulty at the same time. Figure 3.5 depicts a partial plan for observing and repairing a component C_i. The plan begins in a system state where the feature variables have the values $\mathbf{f}_i$ and ends in a goal state or a system state where the feature variables have the values $\mathbf{f}_{i+1}$. First, the component is observed. However, it is possible $\mathbf{F} = \mathbf{f}_i$ does not satisfy the preconditions for the action that observes C_i. Therefore, we must first perform a sequence of actions such that those preconditions can be satisfied, e.g., we may have to assemble or disassemble certain features. Let $\mathcal{A}_i^{obs}$ be such a sequence of actions that also includes the observing action. When the actions in $\mathcal{A}_i^{obs}$ are performed, a system state where $\mathbf{F} = \mathbf{f}_i^{obs}$ is reached. If C_i is non-faulty, a sequence of actions $\mathcal{A}_i'$ is performed to take the system to a state where $\mathbf{F} = \mathbf{f}_{i+1}$. If C_i is faulty, then it is repaired by a sequence of actions $\mathcal{A}_i^{rep}$ and then a function control is made by a sequence of actions $\mathcal{A}_i^{fc}$. If the function control indicates that no more components are faulty, then the sequence of actions $\mathcal{A}_i^g$ is performed that takes us to a system state where the feature variables are that of a goal state $\mathbf{f}_g$. Otherwise, a sequence of actions $\mathcal{A}_i''$ is performed to take the system to a system state where $\mathbf{F} = \mathbf{f}_{i+1}$. Note that this system state is not necessarily the same as the one reached when $C_i = NF$. However, they have in common that the probability that C_i is faulty is zero and that $\mathbf{F} = \mathbf{f}_{i+1}$. Figure 3.6 depicts a similar plan for repairing a component where there is no action that observes it.

In any system state s we can start with a sequence of actions $\mathcal{A}_0'(s)$ that

$$\begin{tikzcd}
 & & & \mathbf{f}_g & & \\
{} \arrow[r, dashed] & \mathbf{f}_i \arrow[r, "\mathcal{A}_i^{rep}"] & \mathbf{f}_i^{rep} \arrow[r, "\mathcal{A}_i^{fc}", "C_i := NF"'] & \mathbf{f}_i^{fc} \arrow[u, "\mathcal{A}_i^{g}", "\forall j, C_j = NF"'] \arrow[r, "\mathcal{A}'_i", "\exists j, C_j \neq NF"'] & \mathbf{f}_{i+1} \arrow[r, dashed, dash] & {}
\end{tikzcd}$$

Figure 3.6: A troubleshooting plan for repairing an unobservable component C_i.

takes us from s to a system state where $\mathbf{F} = \mathbf{f}_1$ and then execute these partial plans in order until all faults are repaired. We call this type of troubleshooting plan for a fixed troubleshooting strategy π_{fixed}. If s is such that no components can be faulty, we start instead with a sequence of actions $\mathcal{A}_0^g(s)$ that takes us to the nearest goal state. If $\mathbf{f}_i = \mathbf{f}_j$ for all i, j these partial plans can be executed in any order.

We will now define two functions $\mathcal{S} \mapsto \mathbb{R}^+$ and six real valued constants that gives the cost of executing parts of the partial plans in a system state s that we will use to create the new heuristic:

$$c'_0(s) = \textstyle\sum_{a \in \mathcal{A}'_0(s)} c(a)$$

$$c_0^g(s) = \textstyle\sum_{a \in \mathcal{A}_0^g(s)} c(a)$$

$$c_i^{obs} = \begin{cases} \sum_{a \in \mathcal{A}_i^{obs}} c(a) & \text{if } C_i \text{ is observable,} \\ \sum_{a \in \mathcal{A}_i^{rep} \cup \mathcal{A}_i^{fc}} c(a) & \text{otherwise,} \end{cases}$$

$$c'_i = \textstyle\sum_{a \in \mathcal{A}'_i} c(a)$$

$$c_i^{rep} = \begin{cases} \sum_{a \in \mathcal{A}_i^{rep}} c(a) & \text{if } C_i \text{ is observable,} \\ 0 & \text{otherwise,} \end{cases}$$

$$c_i^{fc} = \begin{cases} \sum_{a \in \mathcal{A}_i^{fc}} c(a) & \text{if } C_i \text{ is observable,} \\ 0 & \text{otherwise,} \end{cases}$$

$$c_i^g = \textstyle\sum_{a \in \mathcal{A}_i^g} c(a)$$

$$c'' = \begin{cases} \sum_{a \in \mathcal{A}''_i} c(a) & \text{if } C_i \text{ is observable,} \\ \sum_{a \in \mathcal{A}'_i} c(a) & \text{otherwise,} \end{cases}$$

Furthermore, let the ordered set $\mathcal{I}$ be some permutation of $(1, \ldots, |\mathbf{C}|)$ such that $\mathcal{I}(i)$ determines when in order the partial plan for C_i shall be executed. Then we can define a heuristic h_{fixed} as:

$$h_{\mathit{fixed}}(s) = \begin{cases} c_0^g(s) & \text{if } P(C_i = NF) = 1 \text{ for all } C_i \in \mathbf{C} \text{ given } s, \\ c_0'(s) + \sum_{i=1}^{|\mathbf{C}|} \left(p_i^{obs} c_i^{obs} + p_i' c_i' + p_i^{rep}(c_i^{rep} + c_i^{fc}) + p_i^g c_i^g + p_i'' c_i''\right) & \text{otherwise,} \end{cases} \tag{3.45}$$

where

$$\begin{aligned}
p_i^{obs} &= \sum_{\mathbf{c} \in \mathcal{C}_i^{obs}} b(\mathbf{c}), & \mathcal{C}_i^{obs} &= \{\mathbf{c} : \mathbf{c} \in \Omega_{\mathbf{C}}, \exists \mathcal{I}(j) \geq \mathcal{I}(i)\ C_j \neq NF\} \\
p_i' &= \sum_{\mathbf{c} \in \mathcal{C}_i'} b(\mathbf{c}), & \mathcal{C}_i' &= \{\mathbf{c} : \mathbf{c} \in \Omega_{\mathbf{C}}, C_i = NF, \exists \mathcal{I}(j) > \mathcal{I}(i)\ C_j \neq NF\} \\
p_i^{rep} &= \sum_{\mathbf{c} \in \mathcal{C}_i^{rep}} b(\mathbf{c}), & \mathcal{C}_i^{rep} &= \{\mathbf{c} : \mathbf{c} \in \Omega_{\mathbf{C}}, C_i \neq NF\} \\
p_i^g &= \sum_{\mathbf{c} \in \mathcal{C}_i^g} b(\mathbf{c}), & \mathcal{C}_i^g &= \{\mathbf{c} : \mathbf{c} \in \Omega_{\mathbf{C}}, C_i \neq NF, \forall \mathcal{I}(j) > \mathcal{I}(i)\ C_j = NF\} \\
p_i'' &= \sum_{\mathbf{c} \in \mathcal{C}_i''} b(\mathbf{c}), & \mathcal{C}_i'' &= \{\mathbf{c} : \mathbf{c} \in \Omega_{\mathbf{C}}, C_i \neq NF, \exists \mathcal{I}(j) > \mathcal{I}(i)\ C_j \neq NF\}
\end{aligned}$$

Theorem 3.4. Let s be any system state in an SSPP for troubleshooting and let π^* be an optimal policy for the SSPP. Then $h_{\mathit{fixed}}(s) \geq V_{\pi^*}(s)$.

Proof. We begin by proving that $h_{\mathit{fixed}}(s) \geq V_{\pi_{\mathit{fixed}}}(s)$ for any system state s. Each partial plan i can be exited in two ways. Either all components are repaired in which case we exit in a goal state or component i is repaired but more components are faulty, in which case we continue with the partial plan $i+1$. This means that π_{fixed} is a solution to the SSPP and that $V_{\pi_{\mathit{fixed}}}(s) \geq V_{\pi^*}(s)$.

Assume that none of the action sequences have any collateral repair effects, i.e. no sequence of actions will make any other repair than the intended one. Then the probability that a certain path in $\pi_{\mathit{fixed}}(s)$ is taken can be determined from s. A partial plan i will only begin if some component $C_j \neq NF$ where $j \geq i$, i.e. with the probability p_i^{obs}. An observable component will only be repaired if it is faulty, i.e. with the probability p_i^{rep} and we will thereby be finished if C_i was the only remaining faulty component, i.e. with the probability p_i^g. If more faulty components exist, we will continue to the next partial plan with probability p_i''. If an observable component C_i is not faulty but some other component $C_j \neq NF$ where $\mathcal{I}(j) > \mathcal{I}(i)$, then with the probability p_i'' we will perform the actions in $\mathcal{A}_i'$ (the lower path in Figure 3.5). For an unobservable component C_i, instead of observing it, we will perform a sequence of actions that repairs it and makes a function control with the probability p_i^{obs}. The probability of exiting to a goal state and the probability of continuing to the next partial plan will be the same as in the case of an observable component.

If there are collateral repair effects, a component may become repaired prematurely and the expected cost $V_{\pi_{\mathit{fixed}}}(s)$ may become lower than $h_{\mathit{fixed}}(s)$, therefore $h_{\mathit{fixed}}(s) \geq V_{\pi_{\mathit{fixed}}}(s) \geq V_{\pi^*}(s)$ for all states $s \in \mathcal{S}$. $\square$

All the costs c_i^{obs}, c_i', c_i^{rep}, c_i^{fc}, c_i^{g}, and c_i'' are independent of the system state and can thereby be computed off-line. For a system state $s = \langle b_\omega, \mathbf{f}, \mathbf{r}\rangle$, the probabilities p_i^{obs}, p_i', p_i^{rep}, p_i^{g}, and p_i'' can be computed in $\mathcal{O}(|\mathbf{C}||b|)$ time. If the components are ordered in descending order by p_i^{rep}/c_i^{obs} the fixed troubleshooting strategy heuristic will reduce to the heuristic in Heckerman et al. [33] for the case when actions have no preconditions and at most one component can be faulty.

The choice of $\mathbf{f}_i$ may affect the value of the heuristic and it is a good idea to choose some value that fulfills many of the preconditions of the actions that observes an observable component or repairs an unobservable one. Since a function control is not needed when the last component has been repaired, the cost can further be reduced by setting c^{fc} to zero for the last component with non-zero probability of being faulty which yields a tighter upper bound.

Example 3.7. Consider the same initial state as in Example 3.6. If we let $\mathbf{f}_i = \mathbf{f}_g = [\mathit{fit}, \mathit{fit}]$, then $c_0^g(s) = c_0'(s) = 0$. The components C_1 and C_4 are observable and the values for c_i^{obs}, c_i', c_i^{rep}, c_i^{fc}, c_i^{g}, c_i'', p_i^{rep}, and p_i^{rep}/c_i^{obs} for all components are the following:

i	c_i^{obs}	c_i'	c_i^{rep}	c_i^{fc}	c_i^{g}	c_i''	p_i^{rep}	p_i^{rep}/c_i^{obs}
1	35	25	150	65	0	0	0.125	0.0036
2	185	0	0	0	0	0	0.125	$6.7 \cdot 10^{-4}$
3	140	0	0	0	0	0	0.501	0.0036
4	10	0	20	40	0	0	0.376	0.038

When the components are ordered descending by the ratios p_i^{rep}/c_i^{obs}, we get $\mathcal{I} = (3, 4, 2, 1)$. The probabilities p_i^{obs}, p_i', p_i^{g}, and p_i'' are:

i	p_i^{obs}	p_i'	p_i^{g}	p_i''
1	0.251	0.125	0.125	$1.3 \cdot 10^{-4}$
2	0.125	0.0	0.125	0.0
3	0.751	0.250	0.500	0.0010
4	1.0	0.624	0.249	0.127

Using (3.43) we can compute the value for the fixed strategy heuristic to be 199.7.

3.6.4 Assembly Model

There are many reasons why we may choose to perform a specific action. It can be to repair a component that is suspected to be faulty, or to make an observation to learn more of which components may be faulty, but it can also be to affect the feature variables such that the goal state is reached or to satisfy the preconditions of another action that we want to perform. If we only needed to consider which repair or observation we wish to make, solving the planning problem can become easier. When Assumptions 4–6 hold, this is exactly what we can do.

Assumptions 4–6 are plausible for a system where the feature variables correspond to parts of the system that may be obstructing each other such that they must be removed in a specific order. Figure 3.7(a) illustrates this with a set of "building blocks" standing on top of each other. Formally these assumptions can be described like following.

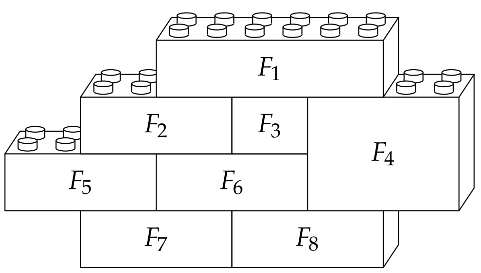
Each feature variable $F \in \mathbf{F}$ has the value space (A, D), i.e. they can either be assembled A or disassembled D. When a certain feature is assembled, certain other features must also, directly or indirectly, be assembled. Likewise, when a certain feature is disassembled, certain other features must also, directly or indirectly, be disassembled. Nothing else is relevant to whether a feature can be assembled or disassembled. This is equivalent to ordering the feature variables in a partial order such that $F_i > F_j$ if F_i must be disassembled before F_j and $F_i < F_j$ if F_i must be assembled before F_j. Let $pa(F) \subset \mathbf{F}$ be the only set of features such that for every $F_i, F_j \in pa(F), F_i > F, F_j > F, \neg(F_i > F_j)$, and $\neg(F_i < F_j)$. Similarly, let $ch(F) \subset \mathbf{F}$ be the largest set of features such that for every $F_i, F_j \in ch(F), F_i < F, F_j < F, \neg(F_i < F_j)$, and $\neg(F_i > F_j)$.

The partial ordering corresponds to a Directed Acyclic Graph (DAG) where the nodes are feature variables and each feature F has the parents $pa(F)$ and the children $ch(F)$. This DAG is called the *assembly graph*. The assembly graph for the example in Figure 3.7(a) is shown in Figure 3.7(b).

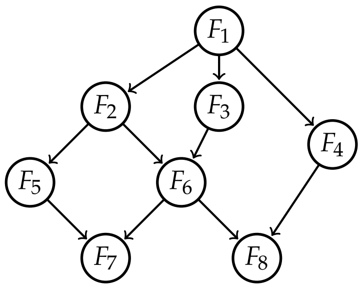
For each $F \in \mathbf{F}$, there exists at least one action that has the effect $F := D$. Such an action will have no other preconditions than $F = A$ and $F' = D$ for all $F' \in pa(F)$. Also, there exists at least one action that has the effect $F := A$. Such an action will have no other preconditions than $F = D$ and $F' = A$ for all $F' \in ch(F)$.

Composite Actions

The assembly graph can be used to generate an optimal sequence of actions to fulfill the preconditions of any other action. If we want to perform a certain action a, but its precondition is not fulfilled in the current system state s, we



(a) In Assumption 6 the features depend on each other like "building blocks"



(b) The assembly graph that describes the dependencies between the feature variables to the left.

Figure 3.7: The dependencies between feature variables.

can combine a with such a sequence of actions forming a macro action called the *composite action* of a. This composite action will then be applicable in s.

Assume that the precondition of an action a can be described by conjunction of expressions $F = f$. Let $\mathcal{P}(a)$ be a set consisting of all these expressions that describe the precondition of a. Let the sequence $\mathcal{E}(a)$ consist of the effects of the action a. Let $\mathit{assemble}(F)$ be the cheapest action that assembles the feature F and let $\mathit{disassemble}(F)$ be the cheapest action that disassembles the feature F. We are interested in the cheapest actions, because from Assumption 6 it follows that no action may have effects that change the values of multiple feature variables. Given the state of the feature variables $\mathbf{f}$, a composite action a' of a can be created using Algorithm 4.

For every precondition in $\mathcal{P}(a)$ of the type $\{F = D\}$ and for every ancestor of F that is not disassembled in $\mathbf{f}$, a disassembling action must be performed. Likewise, for every precondition in $\mathcal{P}(a)$ of the type $\{F = A\}$ and for every successor to F that is not assembled in $\mathbf{f}$, an assembling action must be performed. Algorithm 4 creates a new composite action a' with a cost $c(a')$ that is the combined cost of these actions. The actions are found in the reverse order in which they should be executed. Therefore new effects are added to the beginning of $\mathcal{E}(a')$. The cost $c(a') - c(a)$ is the smallest possible cost of all action sequences that take us from the system state s to a state where the precondition of a is satisfied.

Algorithm 4 Create Composite Action

```
1: procedure CREATECOMPOSITEACTION($M$,$a$,$\mathbf{f}$)
2:     $c(a') \leftarrow c(a)$
3:     $\mathcal{E}(a') \leftarrow \mathcal{E}(a)$
4:     $\mathcal{F}_{queue} \leftarrow \emptyset$
5:     for each $\{F{=}f\} \in \mathcal{P}(a)$ do
6:         if $\{F{=}f\} \notin \mathbf{f}$ then ENQUEUE($\{F'{=}f\}, \mathcal{F}_{queue}$)
7:     end for
8:     while $\mathcal{F}_{queue} \neq \emptyset$ do
9:         $\{F{=}f\} \leftarrow$ DEQUEUE($\mathcal{F}_{queue}$)
10:        if $f = D$ then
11:            $a'' \leftarrow disassemble(F)$
12:            for each $F' \in pa(F)$ do
13:                if $\{F{=}D\} \notin \mathbf{f} \wedge \{F{=}D\} \notin \mathcal{F}_{queue} \wedge \{F{:=}D\} \notin \mathcal{E}(a')$ then
14:                    ENQUEUE ($\{F'{=}D\}, \mathcal{F}_{queue}$)
15:                end if
16:            end for
17:        else
18:            $a'' \leftarrow assemble(F)$
19:            for each $F' \in ch(F)$ do
20:                if $\{F{=}A\} \notin \mathbf{f} \wedge \{F{=}A\} \notin \mathcal{F}_{queue} \wedge \{F{:=}A\} \notin \mathcal{E}(a')$ then
21:                    ENQUEUE ($\{F'{=}A\}, \mathcal{F}_{queue}$)
22:                end if
23:            end for
24:        end if
25:        $c(a') \leftarrow c(a') + c(a'')$
26:        $\mathcal{E}(a') \leftarrow \mathcal{E}(a''); \mathcal{E}(a')$
27:    end while
28: end procedure
```

Applicable Actions

When we use composite actions, the set of possible actions will instead of $\mathcal{A}$ be $\mathcal{A}'$, which is a function of the state. For any state s, $\mathcal{A}'(s)$ will contain the composite action for all actions in $\mathcal{A}$ that have at least one effect that is either a repair, observation, or operation of the system. An action that has preconditions that cannot be represented as a conjunction is replaced by one action for every disjunction that is needed. For example, an action with the precondition $\{F_1 = D\} \vee \{F_2 = D\}$ will be replaced by the actions a_1 and a_2 where $\mathcal{P}(a_1) = \{\{F_1 = D\}\}$ and $\mathcal{P}(a_2) = \{\{F_2 = D\}\}$ respectively. If in a state s, the probability that no component is faulty is one, $\mathcal{A}'(s)$ will also contain a composite action corresponding to the stop action a_0 that sets the feature variables to $\mathbf{f}_g \in \mathcal{F}_g$.

Definition 3.8 defines an action to be applicable in a state s if that action has a non-zero probability of reaching any other state $s' \in \mathcal{S} \setminus \{s\}$ from s. All actions in $\mathcal{A}'(s)$ have their preconditions satisfied in s and cannot be deemed inapplicable for that reason. However, we can rule out further actions that will not be applicable in s. These are actions whose repair effects (if any) repair components with zero probability of being faulty, whose observation effects (if any) observe variables that have a known value or have parents in the BN that all have known values, and whose operation effects (if any) operate the system when no repair events have occurred since the last operation event.

Any optimal solution that is found using only applicable composite actions will be equivalent to any optimal solution that can be found when only ordinary actions are used.

Theorem 3.5. Let π be an optimal solution to the SSPP for troubleshooting $SSPP = \langle \mathcal{S}, \mathcal{A}, p, c, s_0, \mathcal{S}_g \rangle$ and let π' be an optimal solution to the SSPP for troubleshooting $SSPP' = \langle \mathcal{S}, \mathcal{A}', p', c', s_0, \mathcal{S}_g \rangle$ where composite actions are used instead. Then $V_\pi(s) = V_{\pi'}(s)$.

Proof. In any state s, each applicable composite action corresponds to a sequence of applicable ordinary actions. Therefore a version of π' where every composite action is replaced by its constituting actions is a valid solution to $SSPP$ and $V_{\pi'}(s) \geq V_\pi(s)$.

Let $\mathcal{S}' \subseteq \mathcal{S}$ be all states $s \in \mathcal{S}$ that are either in $\mathcal{S}_g$ or such that $\pi(s)$ is an action that either makes an observation, repairs a component, or operates the system. In any state $s \in \mathcal{S}$, using π must lead to a sequence of actions $\mathcal{A}^f(s, s')$ that only affects feature variables that reaches a state s' in $\mathcal{S}'$. Assume that $\mathcal{A}^f(s, s')$ always has minimal cost. Then $\mathcal{A}'(s)$ will contain a composite action a'_s that also reaches s'. A policy π'' where $\pi''(s) = a'_s$ for all $s \in \mathcal{S}'$ will be a solution to $SSPP'$ such that $V_\pi = V_{\pi''}$. The policy π' is optimal, therefore $V_{\pi'} \leq V_{\pi''}$ and $V_{\pi'} = V_\pi$ if $\mathcal{A}^f(s, s')$ has minimal cost for all $s, s' \in \mathcal{S}'$.

Now assume that $V_\pi < V_{\pi'}$. Then it must be so that for some state $s, s' \in \mathcal{S}'$, using π leads to a sequence of actions $\mathcal{A}^f(s, s')$ that does not have minimal cost. We shall prove that for each such case we can create an equivalent policy with the same expected cost where all such sequences are optimal and thereby prove that the assumption $V_\pi < V_{\pi'}$ never can be true. When $\mathcal{A}^f(s, s')$ is suboptimal at least one feature variable F is set from a mode f to a mode f' that is not necessary to satisfy the precondition of $\pi(s')$.

Let a be the last action in $\mathcal{A}^f(s, s')$ that affects a feature variable F that is not necessary to satisfy the precondition of $\pi(s')$. If a disassembles F then it can safely be postponed to after $\pi(s')$ without preventing any other action in $\mathcal{A}^f(s, s')$ from being performed and it will still be applicable because any action that assembles a variable in $pa(F)$ requires F to be assembled which would mean that $\mathcal{A}^f(s, s')$ contains actions that both assemble and disassemble F. This is not possible because then either a is necessary to satisfy the precondition of $\pi(s')$ or a is not the last in $\mathcal{A}^f(s, s')$ that affects a feature variable F that is not necessary to satisfy the precondition of $\pi(s')$. The same reasoning applies if a is an action that assembles F. This means that we can postpone any action that is not necessary to satisfy the precondition of $\pi(s')$ in any state $s' \in \mathcal{S}'$ until they are needed, and thereby we create a policy where all sequences of actions affecting only feature variables have minimal cost. Therefore the assumption $V_\pi < V_{\pi'}$ cannot be true. $\square$

3.7 Relaxing the Assumptions

In this section we will see how some of the assumptions made in Section 3.4 can be relaxed and how this can be treated in the troubleshooting framework.

3.7.1 A Different Repair Goal

Assumption 1 states that all faulty components must be repaired in order to successfully solve the troubleshooting problem. However, in some situations it can be preferred to accept a certain risk of some component still being faulty over doing many more actions to make sure that the system really is fault free.

This can be modeled by extending the troubleshooting model with a set of *loss functions* $l_i : \Omega_{C_i} \mapsto \mathbb{R}^+$ where $l_i(c)$ is the penalty on the cost of repair that is added if it is discovered that the component C_i is in mode c after the troubleshooting session is ended. A special stop action with the precondition that the feature variables should be in the mode $\mathbf{f}_g$ takes us directly to an abstract goal state. The cost of this action c_{stop} will depend on the belief state of the system state s in which troubleshooting is stopped.

$$c_{stop}(s) = \sum_{\mathbf{c}\in\Omega_\mathbf{C}} b(\mathbf{c})l(\mathbf{c}) \tag{3.46}$$

where $l(\mathbf{c}) = \sum_{i=1}^{n} l_i(c_i)$, $\mathbf{c} = (c_1, \ldots, c_n$, and $n = |\mathbf{C}|$.

The loss function can be modeled to reflect things such as bad will, performance loss, or the risk of damaging the system further. For example, the loss function may be high for a fault such as "low engine oil" since this may cause the engine to seize up, but for a fault such as "broken position light" with less severe consequences, the loss function may be lower. Typically $l_i(c)$ is much larger than the cost of repairing C_i.

Relaxing this assumption does not prevent us from solving the troubleshooting problem as an SSPP. Also, this new stopping criterion simplifies the relaxation of certain other assumptions. For example, Assumption 2, repairable components, can unproblematically be relaxed since all components do not necessarily have to be repaired in the goal states.

The assumption that all repairs are perfect, Assumption 3, can also be relaxed. A possible model for imperfect repairs is the following. Let $p_i^f(c)$ be the probability that an attempted repair of a component C_i causes C_i to enter the mode c. Then after a repair event $C_i^t := NF$, the transition probabilities for the component variable C_i^t in the nsDBN for troubleshooting will be

$$P(\mathbf{C}_i^t = c|\mathbf{e}^{1:t-1}; C_i^t := NF, B_{ns}(\mathbf{e}^{1:t})) = p_i^f(c).$$

This means that the intervention on C_i^t still breaks the causal relation between C_i^t and C_i^{t-1} and the Diagnoser can still be used as described in Section 3.5. However, the set of recent repair events $\mathbf{r}$ can no longer be deterministically determined and therefore we must also keep track its distribution. Let $\mathbf{R}^t$ be a stochastic variable with the distribution $P(\mathbf{r}^t|\mathbf{e}^{1:t}, B_{ns})$. When Assumption 3 is relaxed, a system state will contain $\mathbf{R}^t$ instead of $\mathbf{r}^t$ and (3.23) is replaced with

$$b^t(\mathbf{c}) = \sum_{\mathbf{r}\in\Omega_\mathbf{R}} P(\mathbf{r}^t|\mathbf{e}^{1:t}, B_{ns}) \sum_{\bar{\mathbf{c}}\in\Omega_\mathbf{C}} P(\mathbf{c}^t|\bar{\mathbf{c}}^{t_\omega}, \mathbf{r}^t, B_{ns}) b_\omega^t(\bar{\mathbf{c}}), \tag{3.47}$$

(3.24) is replaced with

$$P(e^t|\mathbf{e}^{1:t-1}, \epsilon^t, B_{ns}) = \sum_{\mathbf{r}\in\Omega_\mathbf{R}} P(\mathbf{r}^{t-1}|\mathbf{e}^{1:t-1}, B_{ns}) \sum_{\mathbf{c}\in\Omega_\mathbf{C}} b_\omega^{t-1}(\mathbf{c}) P(X = x|\gamma(\mathbf{r}^{t-1}, \mathbf{c}), \mathbf{c}, \hat{B}), \tag{3.48}$$

and (3.32) is replaced with

$$b_\omega^{t+1}(\mathbf{c}) = \sum_{\mathbf{r}\in\Omega_\mathbf{R}} P(\mathbf{r}^t|\mathbf{e}^{1:t}, B_{ns}) \frac{b_\omega^t(\mathbf{c}) P(X = x|\gamma(\mathbf{r}^t, \mathbf{c}), \mathbf{c}, \hat{B})}{\sum_{\bar{\mathbf{c}}\in\Omega_\mathbf{C}} b_\omega^t(\bar{\mathbf{c}}) P(X = x|\gamma(\mathbf{r}^t, \bar{\mathbf{c}}), \bar{\mathbf{c}}, \hat{B})}. \tag{3.49}$$

The distribution for the set of recent repair events is updated as following:

$$P(\mathbf{r}^{t+1}|\mathbf{e}^{1:t+1}, B_{ns}) = \sum_{\mathbf{r}\in\Omega_{\mathbf{R}}} P(\mathbf{r}^{t+1}|\mathbf{r}^{t}, \mathbf{e}^{1:t+1}, B_{ns}) P(\mathbf{r}^{t}|\mathbf{e}^{1:t+1}, B_{ns})$$

where $P(\mathbf{r}^{t+1}|\mathbf{r}^{t}, \mathbf{e}^{1:t+1}, B_{ns})$ will only be dependent on the latest event e^{t+1} and

$$P(\mathbf{r}^{t}|\mathbf{e}^{1:t+1}, B_{ns}) = \frac{P(e^{t+1}|\mathbf{r}^{t}, \mathbf{e}^{1:t}, B_{ns}) P(\mathbf{r}^{t}|\mathbf{e}^{1:t}, B_{ns})}{P(e^{t+1}|\mathbf{e}^{1:t}, B_{ns})}. \tag{3.50}$$

The equation (3.50) can be computed from (3.24) and (3.48) and the previous distribution for the set of recent repair events.

The Diagnoser can also handle a model where Assumption 10 is relaxed and there is chance that components break down during operation. In the area of reliability engineering, a common model for the failure rate of components is to model component breakdowns with an exponential distribution [22]. Failures, i.e. transitions from a non-faulty mode *NF* to a faulty mode *F*, may occur continuously and independently of each other during operation. A parameter λ_C specifies the failure rate of a component C where $1/\lambda_C$ can be interpreted as the mean time between failures. The probability that a specific component is faulty at time t given that the system is operated for τ time units between the times $t-1$ and t is dependent on the mode of C^{t-1} as:

$$P(C^t = F|c^{t-1}, \omega^t(\tau)) = \begin{cases} 1 - e^{-\lambda\tau} & \text{if } C^{t-1} = NF, \\ 1 & \text{otherwise.} \end{cases}$$

Operating the system twice with the durations τ_1 and τ_2 is the same thing as operating the system once with the duration $\tau_1 + \tau_2$:

$$P(C^t = F|c^{t-2}, \omega^{t-1}(\tau_1), \omega^t(\tau_2)) = P(C^t = F|c^{t-1}, \omega^t(\tau_1 + \tau_2))$$

With the new repair goal, Assumption 11 (function control) can also be relaxed. If we tolerate a certain risks of components being faulty when the troubleshooting ends, it becomes less important to have a test that can verify that the system is guaranteed to be free of faults.

3.7.2 Adapting the Heuristics

After relaxing these assumptions we can still find an optimal troubleshooting plan using the troubleshooting framework. Some of the search heuristics described in Section 3.6.3 are however no longer valid in their current form.

Lower Bound Heuristics

The h_{min}-heuristic is still an admissible lower bound and does not need to be adapted because it is a general heuristic that can be used for any SSPP.

The heuristic h_{ent}, however, is no longer admissible. Taking the penalty $b(\mathbf{c})l(\mathbf{c})$ instead of finding the faults in **c** and repairing them is equivalent with setting $b(\mathbf{c}) = 0$. Therefore, the entropy will be reduced by $-b(\mathbf{c}) \log_2 b(\mathbf{c})$. The cost of reducing the entropy by one in this way is $-l(\mathbf{c})/\log_2 b(\mathbf{c})$ which is a value that can be arbitrarily smaller than $\min_{a \in \mathcal{A}} c_H(a)$ which makes the heuristic non-admissible.

The following new admissible entropy based heuristic $\hat{h}_{ent}$ is proposed to be used instead of h_{ent}:

$$\hat{h}_{ent}(s) = -\sum_{\mathbf{c} \in \Omega_{\mathbf{C}}} b(\mathbf{c}) \log_2 b(\mathbf{c}) \min\Big(\frac{-l(\mathbf{c})}{\log_2 b(\mathbf{c})}, \min_{a \in \mathcal{A}} c_H(a)\Big). \tag{3.51}$$

The imperfect repairs interfere with the h_{fo}-heuristic. If we assume full observability, we can repeat a repair action until the component we want to repair is repaired. This means that the expected cost of repairing a component is increased by at least a factor $(1 - p^f)^{-1}$ where p^f is the probability that the repair fails. Therefore, during the computations of $c(\mathbf{c}, \mathbf{f})$, we will increase the costs of all repair actions by the associated factor.

It may also be the case that it is better to not repair a component and instead take the penalty for leaving it unrepaired. This can be considered in the following way. As before, let $c(\mathbf{c}, \mathbf{f})$ be the minimal cost of repairing the faulty components in **c** and setting the feature values to some $\mathbf{f}_g \in \mathcal{F}_g$ given the values of the feature variables **f**.

The computation of $c(\mathbf{c}, \mathbf{f})$ is as following. Let $\mathbf{c} = (c_1, \ldots, c_n$ and let $\bar{\mathbf{c}}_i$ be the same as **c** except that C_i is in the mode *NF*. If $c(\mathbf{c}, \mathbf{f}) - c(\bar{\mathbf{c}}_i, \mathbf{f}) > l_i(c_i)$ it is better to not repair C_i. Let

$$\hat{c}_i(\mathbf{c}, \mathbf{f}) = \begin{cases} \min\big(l_i(c_i) + \hat{c}_{i+1}(\bar{\mathbf{c}}_i, \mathbf{f}), \hat{c}_{i+1}(\mathbf{c}, \mathbf{f})\big) & \text{if } i < |\mathbf{C}|, \\ \min\big(l_i(c_i), \mathbf{f}), c(\mathbf{c}, \mathbf{f})\big) & \text{if } i = |\mathbf{C}|. \end{cases}$$

Then the optimal cost of either repairing or taking the penalty for the components in **c** is $\hat{c}_1(\mathbf{c}, \mathbf{f})$ and the new full observability heuristic is:

$$\hat{h}_{fo}(s) = \sum_{\mathbf{c} \in \Omega_{\mathbf{C}}} b(\mathbf{c}) \hat{c}(\mathbf{c}, \mathbf{f}) \tag{3.52}$$

A new combined heuristic $\hat{h}_{comb}$ can be formulated using $\hat{h}_{ent}$ and $\hat{h}_{fo}$ instead of h_{ent} and h_{fo}:

$$\begin{aligned}\hat{h}_{comb}(s) &= \hat{h}_{fo}(s) + \\ &+ \max\Big(0, -\sum_{\mathbf{c}\in\Omega_\mathbf{C}} b(\mathbf{c})\big(\log_2 b(\mathbf{c}) + \hat{H}(\mathbf{c})\big)\min\Big(\frac{-l(\mathbf{c})}{\log_2 b(\mathbf{c})}, \min_{a\in\mathcal{A}} c_H(a)\Big)\Big)\end{aligned} \quad (3.53)$$

Upper Bound Heuristics

When all these assumptions are relaxed, even if a function control action is available, the partial plans of the h_{fixed} heuristic become less efficient since any repair or operation of the system may insert new faults. Therefore, we propose another upper bound heuristic based on a fixed troubleshooting strategy that does not rely on function controls.

Let $\mathbf{f}_0$ be the values that the feature variables should be in when each partial plan begins and ends, let p_i^f be the probability that the repair of component C_i fails, and let p_i be the probability that C_i is faulty, i.e.

$$p_i = \sum_{\mathbf{c}\in\mathcal{C}_i} b(\mathbf{c}), \quad \mathcal{C}_i = \{\mathbf{c} : \mathbf{c} \in \Omega_\mathbf{C}, C_i \neq NF\},$$

Further, let c_i^{obs} be the cost of the composite action that observes C_i given the previous state, let c_i^{rep} be the cost of the composite action that repairs C_i given the previous state, and let c^f be the cost of a composite action that sets the feature variables to the values $\mathbf{f}_0$. The last composite action is created from a dummy action that has the precondition that $\mathbf{F} = \mathbf{f}_0$, but it has no cost and no effects. Without loss of generality, assume that each component may either be in the mode non-faulty NF or faulty F. An observable component C_i can be repaired using any of the five following partial plans, P1–P5:

P1 *Observe the component and if the component is faulty repair it. Repeat this until the component is observed to be non-faulty.* If C_i is the first component observed, then the expected cost of the partial plan P1 is

$$c_i^{\mathrm{P1}} = c_i^{obs} + p_i(c_i^{rep} + c_i^{obs})/(1 - p_i^f) + c^f.$$

P2 *Observe the component and if the component is faulty repair it and then accept the risk that the component still may be faulty.* If C_i is the first component observed, then the expected cost of P2 is

$$c_i^{\mathrm{P2}} = c_i^{obs} + p_i(c_i^{rep} + p_i^f l_i(F)) + c^f.$$

P3 *Repair the component and then observe it. If the component is still faulty, then repeat until the component is observed to be non-faulty.*. The expected cost of P3 is

$$c_i^{\mathrm{P3}} = (c_i^{rep} + c_i^{obs})/(1 - p_i^f) + c^f.$$

P4 *Repair the component and then accept the risk that the component still may be faulty.* The expected cost of P4 is

$$c_i^{\mathrm{P4}} = c_i^{rep} + p_i^f l_i(F) + c^f.$$

P5 *Do nothing and accept the risk that the component is faulty.* The expected cost of P5 is

$$c_i^{\mathrm{P5}} = p_i l_i(F) + c^f.$$

For unobservable components, only the last two partial plans, P4 and P5, are applicable.

The fixed troubleshooting strategy, $\hat{\pi}_{fixed}$, is to first observe observable components one by one using either the partial plan P1 or P2. If an observable component is shown to be faulty, we will finish the partial plan for that component and then stop and take the penalty for any remaining faulty components. If none of the observable components are faulty, the strategy is to go through the remaining components using the partial plans P3–P5. The partial plan that is used for each component i is $\arg\min_{j\in[1,5]} c_i^{\mathrm{Pj}}$ for observable components and $\arg\min_{j\in[4,5]} c_i^{\mathrm{Pj}}$ for unobservable components. An observable component for which it is best to use one of the partial plan P3–P5 will be delayed until after all partial plans P1 and P2 have been performed.

Let the ordered set $\mathcal{I}$ be some permutation of $[1, \ldots, |\mathbf{C}|]$ such that the ith partial plan that is executed is the one for component $C_{\mathcal{I}(i)}$. Let n be the number of undelayed observable components that shall be processed with the partial plans P1 or P2. The undelayed observable components are just as before ordered in descending order of p_i/c_i^{obs}. The remaining components are placed last in the order arbitrarily since if none of the first n components are faulty, all the remaining $|\mathbf{C}| - n$ partial plans will be executed regardless of any further observations.

Let $\mathcal{I}(\mathbf{c})$ be the first $i \in \mathcal{I}$ such that $C_i = F$ in $\mathbf{c}$ and let $c_i(\mathbf{c})$ be the expected cost of performing the partial plan for the component C_i when the true diagnosis is $\mathbf{c}$. If the true diagnosis is $\mathbf{c}$, the expected cost of repair using the fixed strategy $\hat{\pi}_{fixed}$ will be

$$c_{fixed}(\mathbf{c}) = \begin{cases} \left(\sum_{i=1}^{\mathcal{I}(\mathbf{c})-1} c^{obs}_{\mathcal{I}(i)}\right) + c_{\mathcal{I}(\mathbf{c})}(\mathbf{c}) + \sum_{i=\mathcal{I}(\mathbf{c})+1}^{|\mathbf{C}|} l(\mathbf{C}_{\mathcal{I}(i)} = c) & \text{if } \mathcal{I}(\mathbf{c}) < n, \\ \left(\sum_{i=1}^{n} c^{obs}_{\mathcal{I}(i)}\right) + \sum_{i=n+1}^{|\mathbf{C}|} c_i(\mathbf{c}) & \text{otherwise,} \end{cases} \tag{3.54}$$

The new fixed strategy heuristic $\hat{h}_{fixed}$ is the expected value of (3.54):

$$\hat{h}_{fixed}(s) = \sum_{\mathbf{c}} b(\mathbf{c}) c_{fixed}(\mathbf{c}) \tag{3.55}$$

Example 3.8. Consider the system state in Example 3.6 and a loss function where $l(C_i \neq NF) = 1100$ for $i = 1, 2, 3, 4$. The partial plans for each component will be $P1, P5, P4, P2$ respectively and they will be executed in the order $\mathcal{I} = [4, 1, 3, 2]$. Then the value of $\hat{h}_{fixed}$ in this state is 271.06 where the values of $c_{fixed}(\mathbf{c})$ for all $\mathbf{c}$ are:

$[c_1$	c_2	c_3	$c_4\,]$	$b(\mathbf{c})$	c_{fixed}
$[NF,$	$NF,$	$NF,$	$NF,]$	0	181
$[failure,$	$NF,$	$NF,$	$NF,]$	0.124	231
$[NF,$	$leakage,$	$NF,$	$NF,]$	0	181
$[failure,$	$leakage,$	$NF,$	$NF,]$	0	181
$[NF,$	$NF,$	$failure,$	$NF,]$	0.500	181
$[failure,$	$NF,$	$failure,$	$NF,]$	$5.0 \cdot 10^{-4}$	1331
$[NF,$	$leakage,$	$failure,$	$NF,]$	0	181
$[failure,$	$leakage,$	$failure,$	$NF,]$	0	2431
$[NF,$	$NF,$	$NF,$	$low]$	0.249	30.2
$[failure,$	$NF,$	$NF,$	$low]$	$2.5 \cdot 10^{-4}$	1130.2
$[NF,$	$leakage,$	$NF,$	$low]$	$1.2 \cdot 10^{-4}$	1130.2
$[failure,$	$leakage,$	$NF,$	$low]$	$8.0 \cdot 10^{-5}$	2230.2
$[NF,$	$NF,$	$failure,$	$low]$	0.0010	1130.2
$[failure,$	$NF,$	$failure,$	$low]$	$1.0 \cdot 10^{-6}$	2230.2
$[NF,$	$leakage,$	$failure,$	$low]$	$5.0 \cdot 10^{-4}$	2230.2
$[failure,$	$leakage,$	$failure,$	$low]$	$5.0 \cdot 10^{-7}$	3330.2

3.7.3 General Feature Variables

By relaxing Assumptions 4–6, one could consider features that impose more general preconditions. Then the composite actions can no longer be used. It is possible however to create composite actions by solving the preconditions using an efficient algorithm for classical planning. This is for example done in [79]. In this case however, we cannot guarantee optimality as with Theorem 3.5.

3.7.4 Different Probabilistic Models

It is also possible to consider other types of probabilistic models for the Diagnoser. As long as it is possible to have some efficient state representation and compute (3.10) the same planner can be used in the troubleshooting framework. If also the probabilities $P(\mathbf{c}^t|\mathbf{e}^{1:t}, M_P)$ can be computed efficiently many of the search heuristics can be used as they are. However, extending the framework to be able to use other probabilistic models than the nsDBN:s for troubleshooting is not explored further in this thesis.

3.8 Summary

This chapter presented how the troubleshooting problem is modeled in the troubleshooting framework. The troubleshooting model specifies which components the system is composed of and in which ways they can be faulty, which observations that can be made, what actions that can be performed, and which probabilistic model is used. The probabilistic model describes how components, observations, and events depend on each other. We have showed how an nsDBN for troubleshooting [56] can be used as a probabilistic model for a system where the assumptions presented in Section 3.4.3 are applicable. By using the method presented in Section 3.5.2, the nsDBN for troubleshooting can be represented with a two-layer static Bayesian network. Theorem 3.1 shows that this network can be used instead of the explicit nsDBN to answer queries of the type that are needed by the Diagnoser in the framework.

In Section 3.6.1, we showed that the troubleshooting problem can be transformed into an SSPP. Once we have formulated the troubleshooting problem as an SSPP, any general algorithm for solving SSPP:s can be used. Many state-of-the-art SSPP algorithms such as BRTDP [46], FRTDP [76], and VPI-RTDP [67] use search heuristics that give both an optimistic and a pessimistic estimate of the expected cost. The new heuristics h_{comb} and h_{fixed} are such heuristics for the troubleshooting problem. By grouping actions together into composite actions as described in Section 3.6.4, the set of possible actions can be reduced. Theorem 3.5 shows that any optimal solution found using composite actions will have the same expected cost as the optimal solutions for the general problem without composite actions.

4 Planning Algorithm

In Section 3.6.1 we showed that the troubleshooting problem can be formulated as an SSPP where successor states and transition functions are computed by the Diagnoser. This means that the troubleshooting problem can be solved by general algorithms for SSPP:s.

Many efficient algorithms for solving SSPP:s use search heuristics that give both pessimistic and optimistic estimates for of the optimal expected solution cost and as described in Section 3.6.3, we can formulate such heuristics for the troubleshooting problem. In the literature there exist three such algorithms that are all extensions of the Real Time Dynamic Programming algorithm (RTDP) [2] described in Section 2.3.4. These are Bounded RTDP (BRTDP) [46], Focussed RTDP (FRTDP) [76], and Value of Perfect Information RTDP (VPI-RTDP) [67].

A lower bound of the optimal value function is used to define the policy in each state and an upper bound of the optimal value function is used to help decide if a state has converged or not. In both BRTDP and FRTDP, states with large difference in lower and upper bounds are given priority in the RTDP trials. In BRTDP, the trials are randomized processes while in FRTDP they are deterministic. The algorithm VPI-RTDP uses a slightly different approach. Here, successor states are chosen based on an estimate of the expected improvement in decision quality when updating the state's value.

These algorithms have been shown to converge toward an optimal solution fast requiring relatively few backups on several MDP benchmark problems. However, in certain problems such as the troubleshooting problem, they explore a larger search space and expand more states than necessary. For the troubleshooting problem this is troublesome because state expansions require that the Diagnoser makes inference in a Bayesian network. Compared to state backups, this is a much more computationally intensive operation.

In this chapter, we present a new algorithm for solving SSPP:s, Iterative Bounding LAO* (IBLAO*). It is a general algorithm that is suitable for SSPP:s with characteristics similar to those of the troubleshooting problem.

4.1 Iterative Bounding LAO*

The new algorithm is based on LAO* [31]. IBLAO* maintains two-sided bounds on the optimal solution cost and uses these to prune search branches when the error bound on the optimal solution cost is below a certain threshold. To perform well in an on-line setting this threshold is dynamically changed, starting with a high value that is successively reduced as better solutions are found. The most recent bounds on the optimal solution cost are always available and the user may use this information to decide when to stop the search.

Algorithm 5 shows the IBLAO* algorithm. Throughout this algorithm, whenever a state s is visited for the first time a lower bound f_l and an upper bound f_u of the optimal expected cost are calculated such that $f_l(s) \leq V_{\pi^*}(s) \leq f_u(s)$ using the heuristic functions h_l and h_u respectively.

In line 2, an initial search graph $G' = (\mathcal{N}', \mathcal{E}')$ is created, consisting only of the initial state s_0. The outer loop in lines 3–15 continues indefinitely until stopped by the user. In line 4 the error threshold $\bar{\epsilon}$ is initialized to be a factor $\alpha < 1$ times the current error bound $\hat{e}(s_0)$ in the initial state. The computation of the error bound is described in Section 4.1.2.

The inner loop in lines 5–14 is similar to the LAO* algorithm (Section 2.3.4, Algorithm 3) where fringe states are expanded until a partial policy is found such that the initial state is solved within the current required bound, i.e. $\hat{e}(s_0) \leq \bar{\epsilon}$. The solution graph for the lower bound policy π_l is $G'_{\pi_l} = (\mathcal{N}'_{\pi_l}, \mathcal{E}'_{\pi_l})$. The set $\Phi(G'_{\pi_l})$ consists of each leaf state s in G'_{π_l} where $\hat{e}(s) > \bar{\epsilon}$ and consequently s is not yet solved within the current error bound. If $\Phi(G'_{\pi_l}) \neq \emptyset$, we select a subset $\mathcal{S}_{expand}$ of $\Phi(G'_{\pi_l})$ that is expanded as described in Section 4.1.3. When a state is expanded, all successors to that state are inserted in G' and the lower and upper bounds for the successor states are calculated.

After the expansions on line 6, all ancestors of the newly expanded states, $ancestors(\mathcal{S}_{expand})$, are backed up (line 13). During backups, the bounds, f_l and f_u, and the lower and upper bound policies π_l and π_u are updated. Instead of performing value iteration until convergence as in LAO*, only a single backup is performed over the set of all ancestors of the newly expanded states, $ancestors(\mathcal{S}_{expand})$. Since we already have bounds on the optimal expected cost, the convergence is not necessary to have a provable bound. Much of the total convergence can be obtained with only one backup per state if states far from the initial state are backed up first. If $\Phi(G'_{\pi_l})$ is empty at line 14, the states in G'_{π_l} are backed up until either the estimated error of the initial state $\hat{e}(s_0) \leq \bar{\epsilon}$ or G'_{π_l} changes so that unsolved nodes appear among the leaves. States are never backed up twice in the same iteration and again, states far from the initial state are backed up first. The policy that is returned is the upper bound policy π_u where $V_{\pi_u}(s_0) \leq (1 + \hat{e}(s_0))V_{\pi^*}$.

4.1.1 Evaluation functions

IBLAO* maintains lower and upper bounds of the optimal expected cost for each state s in the explicit graph G'. The current values of these bounds are denoted by $f_l(s)$ and $f_u(s)$, respectively. The lower and upper bound policies π_l and π_u corresponding to these evaluation functions are defined as follows:

$$\pi_l(s) = \arg\min_{a \in \mathcal{A}} T_a f_l(s), \qquad \pi_u(s) = \arg\min_{a \in \mathcal{A}} T_a f_u(s).$$

Every time a new unvisited state is added to G', its bounds are initialized using two heuristic functions: $f_l(s) = h_l(s)$ and $f_u(s) = h_u(s)$. These heuristics are assumed given as part of the problem and must satisfy $h_l(s) \leq V_{\pi^*}(s)$ and $h_u(s) \geq V_{\pi^*}(s)$ for all states s.

When a state is backed up, new bounds $f'_l(s)$ and $f'_u(s)$ are calculated from the previous f-values as follows:

$$f'_l(s) = \max\left(f_l(s), T_{\pi_l(s)} f_l(s)\right) \tag{4.1}$$

$$f'_u(s) = \min\left(f_u(s), T_{\pi_u(s)} f_u(s)\right) \tag{4.2}$$

The bounds guarantee that there *exists* a policy π such that $f_l(s) \leq V_\pi(s) \leq f_u(s)$. However, they do not tell us *how* such a policy can be found.

Theorem 4.1. If the upper bound heuristic h_u is *uniformly improvable*, i.e. for all states s

$$h_u(s) \geq \min_{a \in \mathcal{A}} T_a h_u(s), \tag{4.3}$$

then the value function of the upper bound policy V_{π_u} is bounded by f_l and f_u, so that for all states s $f_l(s) \leq V_{\pi_u}(s) \leq f_u(s)$.

Proof. Since $f_l(s) \leq V_{\pi^*}(s)$, we also have that $f_l(s) \leq V_{\pi_u}(s)$. Assume that

$$f_u(s) \geq \min_{a \in \mathcal{A}} T_a f_u(s). \tag{4.4}$$

Algorithm 5 Iterative Bounding LAO*

```
1: procedure IBLAO*($SSPP = \langle \mathcal{S}, \mathcal{A}, p, c, s_0, \mathcal{S}_g \rangle$ ,$h_l$,$h_u$,$\alpha$)
2:     $G' = (\mathcal{N}', \mathcal{E}') \leftarrow (\{s_0\}, \emptyset)$
3:     while $\neg$stop do
4:         $\bar{\epsilon} \leftarrow \alpha \cdot \hat{\epsilon}(s_0)$
5:         while $\hat{\epsilon}(s_0) > \bar{\epsilon} \wedge \neg$stop do
6:             if $\Phi(G'_{\pi_l}) \neq \emptyset$ then
7:                 $\mathcal{S}_{expand} \leftarrow$ subset of $\Phi(G'_{\pi_l})$
8:                 for each $s \in \mathcal{S}_{expand}$ do EXPAND$(s)$
9:                 $\mathcal{S}_{backup} \leftarrow ancestors(\mathcal{S}_{expand})$
10:            else
11:                $\mathcal{S}_{backup} \leftarrow \mathcal{N}'_{\pi_l}$
12:            end if
13:            for each $s \in \mathcal{S}_{backup}$ do DOBACKUP$(s)$
14:        end while
15:    end while
16:    return $\pi_u$
17: end procedure

18: procedure EXPAND($s$)
19:     for each $a \in A$ do
20:         for each $s' \in succ(a,s) : s' \notin \mathcal{N}'$ do
21:             $f_l(s') \leftarrow h_l(s')$
22:             $f_u(s') \leftarrow h_u(s')$
23:         end for
24:         $\mathcal{N}' \leftarrow \mathcal{N}' \cup \{succ(a,s)\}$
25:         $\mathcal{E}' \leftarrow \mathcal{E}' \cup \{(s, succ(a,s))\}$
26:     end for
27: end procedure

28: procedure DOBACKUP($s$)
29:     $f_l(s) = \min_{a \in \mathcal{A}} T_a f_l(s)$
30:     $\pi_l(s) = \arg\min_{a \in \mathcal{A}} T_a f_l(s)$
31:     $f_u(s) = \min_{a \in \mathcal{A}} T_a f_u(s)$
32:     $\pi_u(s) = \arg\min_{a \in \mathcal{A}} T_a f_u(s)$
33: end procedure
```

Then after applying (4.2) on a state s', $f'_u(s') = T_{\pi_u(s')} f_u(s') \geq \min_a T_a f'_u(s')$ and for all other states s, $f'_u(s) \geq \min_a T_a f_u(s) \geq \min_a T_a f'_u(s)$. Since f_u is initialized with h_u, the condition (4.3) implies that (4.4) holds. Let $f_0, f_1, \ldots$ be functions such that

$$f_i(s) = \begin{cases} V_{\pi^*}(s) & \text{if } i = 0 \text{ or } s \text{ is a goal state,} \\ T_{\pi_u(s)} f_{i-1}(s) & \text{otherwise.} \end{cases}$$

This corresponds to the value function of a policy where actions are chosen according to π_u until i steps into the future when actions are chosen according to π^*. As $i \to \infty$, $f_i(s) \to V_{\pi_u}(s)$. If $i > 0$ and $f_{i-1}(s) \leq f_u(s)$, then using (4.4) $f_i(s) \leq T_{\pi_u(s)} f_u(s) \leq f_u(s)$. Because $f_0(s) = V_{\pi^*}(s) \leq f_u(s)$, it follows that $f_i(s) \leq f_u(s)$ for all i. □

Theorem 4.1 guarantees that the cost of the upper bound policy is always less than or equal to $f_u(s)$ for all s. No such guarantee exists for the lower bound policy. Also, since we have bounds on V_{π_u}, the final value iteration step of LAO* is not needed.

4.1.2 Error Bound

The relative error in a state s is the relative difference between the expected costs of the upper bound policy and the optimal policy in that state:

$$\epsilon(s) = \frac{|V_{\pi_u}(s) - V_{\pi^*}(s)|}{V_{\pi^*}(s)}. \tag{4.5}$$

A state s is considered solved if $\epsilon(s)$ is smaller than the current error threshold $\bar{\epsilon}$. The true relative error is not known since we do not know the exact values for $V_{\pi_u}(s)$ and $V_{\pi^*}(s)$. The value of $V_{\pi^*}(s)$ is bounded by $f_l(s)$ and $f_u(s)$ and using Theorem 4.1 we know that $f_u(s) \geq V_{\pi_u}(s)$ for all states s. Therefore, we can bound the relative error with an estimate:

$$\hat{\epsilon}(s) = \frac{f_u(s) - f_l(s)}{f_l(s)} \geq \frac{V_{\pi_u}(s) - V_{\pi^*}(s)}{V_{\pi^*}(s)} = \epsilon(s).$$

When all successor states of a state s are considered solved, s will also be considered solved after being backed up.

Theorem 4.2. Let s be a state and let $\hat{\epsilon}(s') \leq \bar{\epsilon}$ for all $s' \in succ(s, \pi_l(s))$. Then backing up s will ensure that $\hat{\epsilon}(s) < \bar{\epsilon}$.

Proof. By (4.1) and (4.2), we have that

$$f'_l(s) \geq T_{\pi_l(s)} f_l(s)$$

and

$$f'_u(s) \leq T_{\pi_u(s)} f_u(s) \leq T_{\pi_l(s)} f_u(s)$$

for all states s. Since $\hat{e}(s') \leq \bar{\epsilon}$ for all $s' \in succ(s, \pi_l(s))$,

$$f_u(s') \leq (1 + \bar{\epsilon}) f_l(s')$$

and thereby

$$f'_u(s) \leq (1 + \bar{\epsilon}) T_{\pi_l(s)} f_l(s) - \bar{\epsilon} c(\pi_l(s), s).$$

Finally,

$$\hat{e}(s) = \frac{f'_u(s) - f'_l(s)}{f'_l(s)} \leq \bar{\epsilon} \frac{T_{\pi_l(s)} f_l(s) - c(\pi_l(s), s)}{T_{\pi_l(s)} f_l(s)} < \bar{\epsilon}. \qquad \square$$

When $\Phi(G'_{\pi_l}) = \emptyset$, the estimated error in all leaves of G'_{π_l} is less than or equal to $\bar{\epsilon}$. In this case, if the error bound has not converged so that $\hat{e}(s_0) \leq \bar{\epsilon}$, repeated backups of all the states in G'_{π_l} will either cause $\Phi(G'_{\pi_l}) \neq \emptyset$ or, by Theorem 4.2, cause $\hat{e}(s_0) \leq \bar{\epsilon}$.

When $\hat{e}(s_0) \leq \bar{\epsilon}$ the inner loop is exited and the error threshold $\bar{\epsilon}$ is reduced by a factor α where $0 < \alpha < 1$. Then the algorithm restarts on line 5 and expands states previously considered solved on the fringe of G'_{π_l}.

4.1.3 Expanding the Fringe

Since Iterative Bounding LAO* does not use depth first trials like many RTDP-based algorithms, the fringe may become very large. In each iteration of the inner loop, the algorithm therefore only selects a subset $\mathcal{S}_{expand}$ of the states in $\Phi(G'_{\pi_l})$ for expansion.

Ideally, the algorithm should select those states whose expansions would have the largest impact on the estimated error of the initial state. Omitting such states may lead to unnecessarily many backups, while including other states leads to unnecessary work during expansion. A possible measure of this impact is the product of the estimated error in a state and the likelihood that the state will be reached from s_0 in the solution graph G'_{π_l}.

Since calculating exact state likelihoods is computationally expensive, we use an approximation $\hat{p}(s)$. The calculation of this approximation is interleaved with the calculation of the fringe itself as shown in Algorithm 6, and does not increase the computational complexity of finding the fringe. We then select those states that have an impact higher than the average:

$$\hat{e}(s)\hat{p}(s) \geq \sum_{s' \in G'_{\pi_l}} \hat{e}(s')\hat{p}(s') \Big/ |G'_{\pi_l}| \qquad (4.6)$$

Algorithm 6 Algorithm for calculating the set $\Phi(G'_{\pi_l})$ and the likelihoods $\hat{p}(s)$ for all states $s \in \Phi(G'_{\pi_l})$.

```
1: procedure FINDFRINGE($G'_{\pi_l} = (\mathcal{N}'_{\pi_l}, \mathcal{E}'_{\pi_l})$)
2:     for each $s \in \mathcal{N}'_{\pi_l}$ do $\hat{p}(s) \leftarrow 0$
3:     $\hat{p}(s_0) \leftarrow 1$
4:     $\Phi \leftarrow \emptyset$
5:     $queue \leftarrow (s_0)$
6:     while $queue$ has elements do
7:         $s \leftarrow$ first element in $queue$
8:         for each $s' \in succ(s, \pi_l(s))$ do
9:             $\hat{p}(s') \leftarrow \hat{p}(s') + \hat{p}(s)P(s'|s, \pi_l(s))$
10:            if $\hat{e}(s') > \bar{e}$ then
11:                if $s'$ has successors then add $s'$ to $queue$
12:            else
13:                add $s'$ to $\Phi$
14:            end if
15:        end for
16:    end while
17: end procedure
```

4.1.4 Weighted Heuristics

Just as with A* and LAO*, weighting the heuristic allows Iterative Bounding LAO* to make a trade-off between solution quality and the size of the explored search space. A separate evaluation function f_w is used for the weighted heuristic. For unexpanded states s, $f_w(s) = wh_l(s)$, where the weight $w > 1$. Using this evaluation function, a third policy π_w is defined where

$$\pi_w(s) = \arg\min_{a \in \mathcal{A}} T_a f_w(s).$$

When a state s is backed up, f_w is updated as $f'_w(s) = T_{\pi_w(s)} f_w(s)$.

During search, instead of expanding states in G'_{π_l}, states are expanded from the solution graph of the weighted policy G'_{π_w}. When the weight is high, policies with many fringe states close to the goal where the heuristic estimates of the expected cost to go are smaller will be chosen before less explored policies. This reduces the size of the search space, but may cause optimal solutions to be missed. As with LAO*, in the worst case, the algorithm may converge towards a solution that is suboptimal by a factor w, and for all states s,

$$f_w(s) \leq wV_{\pi^*}(s). \tag{4.7}$$

The error bounds in states are estimated with the weighted estimated error $\hat{\epsilon}_w$, where

$$\hat{\epsilon}_w(s) = \frac{f_u(s) - f_w(s)}{f_w(s)}.$$

Theorem 4.3. If

$$\hat{\epsilon}_w(s) \leq \frac{\bar{\epsilon} + 1}{w} - 1 \tag{4.8}$$

holds, then the relative error $\epsilon(s) \leq \bar{\epsilon}$.

Proof. Using Theorem 4.1 and (4.7),

$$\hat{\epsilon}_w(s) = \frac{f_u(s) - f_w(s)}{f_w(s)} \geq \frac{V_{\pi_u}}{wV_{\pi^*}} - 1.$$

Then using (4.8) and (4.5),

$$\frac{\epsilon(s) + 1}{w} - 1 \leq \frac{\bar{\epsilon} + 1}{w} - 1. \qquad \square$$

Theorem 4.3 makes it possible to choose a weight $w \leq \bar{\epsilon} + 1$ such that when a solution is found in G_{π_w} the relative error is still less than or equal to $\bar{\epsilon}$. There is some freedom in how the weight w may be assigned. If $w = \bar{\epsilon} + 1$ all excess error is used for the weight function and a state s will not be considered solved until $\hat{\epsilon}_w(s) = 0$, forcing the algorithm to expand every state in G_{π_w}. We use $w = \sqrt{\bar{\epsilon} + 1}$, which ensures that search branches can be pruned when $\hat{\epsilon}_w(s) \leq \sqrt{\bar{\epsilon} + 1}$. This choice distributes the amount of acceptable error given by $\bar{\epsilon}$ evenly between w and $\hat{\epsilon}_w(s)$.

When the error threshold $\bar{\epsilon}$ is decreased after the inner loop of Iterative Bounding LAO* has completed, the value of the weight is updated as $w = \sqrt{\bar{\epsilon} + 1}$. In the next iteration, the explicit search graph $G' = (\mathcal{N}', \mathcal{E}')$ cannot be reused directly because (4.7) only holds for the previous value of w.

In each state s we store the value $w(s)$, which is the value of w used by the algorithm the previous time s was visited. Let $\mathcal{S}^w = \{s \in \mathcal{N}' : w(s) = w\}$ where w is the current weight. Any state $s' \notin \mathcal{S}^w$ will be considered unexpanded. However, the information in G' is kept. Therefore, if a state $s \in \Phi(G'_{\pi_w})$ that is to be expanded has already been expanded before, the old values of $f_l(s)$ and $f_u(s)$ are reused and the new value of the weighted evaluation function $f'_w(s)$ is computed as follows:

$$f'_w(s) = \max\left(\frac{w}{w(s)} f_w(s), f_l(s)\right).$$

4.2 Evaluation of Iterative Bounding LAO*

The new algorithm is evaluated against three other state-of-the-art algorithms for SSPP:s that also use two-sided bounds: FRTDP, BRTDP, and VPI-RTDP. It is also compared with ILAO*[31] which is a more efficient version of LAO* that only performs the Value Iteration step when a complete solution is found. Also, in this evaluation, ILAO* is altered so that it, just as the other algorithms, maintains an upper bound function that can be used to extract a policy anytime if needed.

All algorithms have been carefully implemented in Java according to the authors' specifications [31, 46, 67, 76]. For a fair comparison as possible they all use the same data structures for representing states and the same methods for expanding and evaluating states. The algorithms are run using a 2.40 GHz Intel Core2 Duo P8600 CPU where the Java Virtual machine is allowed a maximum heap size of 1600 MB.

For these algorithms, the main contributors to the total computation time are the number of backups and the number of state expansions. An algorithm that does many backups between expansions may select the states to expand more carefully and thereby reduce the search space while an algorithm that selects states to back up more carefully may explore a larger search space faster. The algorithms are compared on problems from two sets of benchmarks publicly available in the literature. In Chapter 5, we will also evaluate IBLAO* for the troubleshooting problem.

The first set of benchmark problems is from the *racetrack* domain [2] which is a common benchmark problem for stochastic shortest path problems. This domain has been used for empirical evaluations of many algorithms similar to Iterative Bounding LAO* [31, 46, 67, 76]. Characteristic for problems from this domain is that their solutions contain many cycles, the actions have unit costs, the branching factor is low, and that new states can be generated quickly.

The second set of benchmark problems are from the *rovers* domain [11] which is a benchmark for probabilistic conditional non-deterministic planning. Characteristic for problems from this domain is that their solutions contain few cycles, the actions have heterogeneous costs, and the branching factor is high.

4.2.1 Racetrack

The racetrack domain was first presented in Barto et al. [2]. The task is to drive a vehicle from a starting position to a goal position. The states are integer vectors $s = (x, y, \dot{x}, \dot{y})$ describing the vehicle's position and velocity in two dimensions. Actions are integer accelerations $a = (\ddot{x}, \ddot{y})$ where $\ddot{x}, \ddot{y} \in \{-1, 0, 1\}$. The states are fully observable, and uncertainty is introduced when actions are performed. If a wall is hit, the vehicle is instantly moved back to the starting position and its velocity is set to zero. A goal state is reached if the vehicle crosses a goal position. The state resulting from performing an action is easily computed by adding the velocity to the position, the acceleration to the velocity, and by making simple check whether a straight line between the current position and the next position is blocked by a wall or a goal position. The racetrack domain is a domain where the RTDP-based algorithms have been shown to be especially successful. The deep RTDP-trials in combination with low branching factor allows them to converge toward an optimal solutions with few backups. We expect IBLAO* to do fewer expansions, but more backups. In the racetrack domain, state expansions are as easily computed as state backup and therefore, we expect the RTDP-based algorithms to be faster in this domain.

We have used two racetrack maps, *large-b* and *block80*, that have been published in Barto et al. [2] and Sanner et al. [67] respectively. The action dynamics are specified as in Smith and Simmons [76] where in *large-b* actions may fail, causing the vehicle to skid and have zero acceleration and in *block80* a perturbing gust of wind may accelerate the vehicle in a random direction. The probability with which an action fails is 0.1. The lower bound heuristic used is the $h_{\min}$ heuristic where for non-goal states s,

$$h_l(s) = h_{\min}(s) = \min_{a \in \mathcal{A}} \Big(c(a,s) + \min_{s' \in succ(a,s)} h_{\min}(s') \Big),$$

and for goal states s, $h_l(s) = 0$. This is the optimal cost if action outcomes could be chosen freely. This heuristic has previously been used for problems from the racetrack domain [9, 76]. The upper bound heuristic is a constant, 1000, for all non-goal states. This is a gross overestimate of the optimal expected cost. This heuristic is in general not uniformly improvable. However, by introducing a special "plan more" action with a cost of 1000 that takes the vehicle directly to the goal, Theorem 4.1 will be applicable.

For each algorithm in the experiment, values of the upper and lower bounds in the initial state are available at any time. When these values have converged so that their relative difference is less than a threshold ϵ the algorithm is halted and the time in seconds and the total number of expansions and back-ups are registered. Also, the expected cost of the current upper bound policy V_{π_u} is evaluated since this represents the actual quality of the policy that is returned from the algorithm.

Two versions of Iterative Bounding LAO* are tested: a weighted version (wIBLAO*) and an unweighted version (IBLAO*). Both uses $\alpha = 0.5$ and wIBLAO* uses $w(\bar{\epsilon}) = \sqrt{1 + \bar{\epsilon}}$. BRTDP uses $\tau = 50$, FRTDP uses $\epsilon = 0.001$, $D_0 = 10$, and $k_D = 1.1$, and VPI-RTDP uses $\alpha = 0.001$ and $\beta = 0.95$. These

Table 4.1: Comparison of algorithms on racetrack *large-b*.

large-b	ϵ	V_{π_u}	*expansions*	*backups*	*time*
wIBLAO*	0.1	23.95	**2606**	108064	0.53
	0.01	23.31	**3743**	203323	1.00
	0.001	23.26	**4353**	286681	1.39
IBLAO*	0.1	24.86	3381	56766	0.45
	0.01	23.45	3995	86356	0.53
	0.001	23.27	4706	120142	0.78
ILAO*	0.1	23.28	9133	342745	0.74
	0.01	23.25	9884	811285	1.49
	0.001	23.25	9909	902720	1.64
BRTDP	0.1	23.48	5527	**33800**	**0.23**
	0.01	23.27	6416	**48270**	**0.28**
	0.001	23.25	6800	**58586**	**0.33**
FRTDP	0.1	23.61	5354	53242	0.30
	0.01	23.27	6565	76546	0.38
	0.001	23.25	7246	96844	0.47
VPI-RTDP	0.1	23.63	5357	57528	0.31
	0.01	23.29	6053	98088	0.44
	0.001	23.25	6768	160680	0.66

are the same values used in the empirical evaluations in [46, 67, 76].

The results are shown in Tables 4.1 and 4.2. The best results in each category are in bold. The best performance is obtained with BRTDP and Iterative Bounding LAO* requires more back-ups than the other algorithms but fewer states are expanded. This is an expected result because IBLAO* backs up all ancestor states to the expanded states while the RTDP algorithms only back up the states on the trajectory of the last trial. Since the vehicle is moved back after it hits a wall, the ancestor states to the initial state make up almost the entire state space. ILAO* will try to expand all states that are reachable given the current lower bound policy. For *block80* almost the entire state space is reachable under the optimal policy. Therefore it is not able to return any solution at all before it runs out of memory (1600 MB). IBLAO* would have this problem too if it expanded all states on the fringe instead of using (4.6). The weighted version of Iterative Bounding LAO* is more restrictive with expansions but requires more back-ups because of the necessary weight adjustments.

Table 4.2: Comparison of algorithms on racetrack *block80*.

block80	ϵ	V_{π_u}	*expansions*	*backups*	*time*
wIBLAO*	0.1	9.81	**10898**	157913	3.38
	0.01	9.61	18642	321675	6.51
	0.001	9.59	**24594**	481827	9.30
IBLAO*	0.1	10.04	12576	227177	4.55
	0.01	9.61	**17232**	318582	6.31
	0.001	9.59	25614	475370	9.42
ILAO*	0.1	-	-	-	-
BRTDP	0.1	9.66	21270	110288	2.95
	0.01	9.59	33423	193632	4.88
	0.001	9.59	41830	**270170**	6.55
FRTDP	0.1	9.65	26985	175120	3.75
	0.01	9.59	41795	295436	5.88
	0.001	9.59	56126	447364	8.08
VPI-RTDP	0.1	9.69	20490	**107640**	**2.91**
	0.01	9.59	32553	**192490**	**4.77**
	0.001	9.59	41058	272936	**6.36**

4.2.2 Rovers Domain

In the Rovers domain, the surface of the planet Mars is explored with a small planetary rover, an autonomous ground vehicle. The rover can move around between different locations on the planet and collect soil and rock samples to be analyzed. It can also take photos of an objective if that objective is visible from the rover's location. If a base station is visible from the rover's location it can communicate the results of the rock and soil analysis as well as any images it has taken back to earth. However, the rover does not always know which locations are visible from each other and where interesting rock and soil samples may be. Therefore, the rover may need to perform sensory actions to detect this.

In Bryce and Kambhampati [11], six different problems from this domain are specified with increasing difficulty. In all problems except *rover1*, the rover does initially not know the exact locations of interesting samples and which locations are visible from each other. In the problems the goals are one or more of the following: have communicated data of a soil sample, have communicated data of a rock sample, or have communicated data of an image taken of objective *o* using camera mode *m*.

Compared to the racetrack domain, the number of possible actions to perform is much greater in the rovers domain. The number of fluents, actions, and goals, as well as the average plan depth of the optimal solution for each problem is listed below:

Problem	*rover1*	*rover2*	*rover3*	*rover4*	*rover5*	*rover6*
No. of fluents	68	68	68	68	68	119
No. of actions	100	100	100	100	100	235
No. of goals	1	1	1	1	3	3
Average depth	5	6.5	6.33	7.5	16	18.33

We will evaluate the algorithms in the same way as in the previous section for six problem instances from the rovers domain with increasing difficulty. The lower bound heuristic will be the full observability heuristic h_{fo} which is a better heuristic than the h_{min} for this domain. The upper bound will be a constant value of 10000.

The results are shown in Tables 4.3–4.5. For the first four problems we only show the results for $\epsilon = 0.001$ since these problems were easily solved by all algorithms. For the more difficult problems we show the results when the algorithms have found solutions with provable error bounds of 0.1, 0.01, and 0.001 respectively.

We see that the weighted variant of IBLAO* is the fastest for all problems and all error thresholds except the tightest error thresholds where the unweighted variant of IBLAO* is slightly faster. However, for the larger thresholds, the difference between the unweighted and the weighted variant of IBLAO* is significant. This is because the upper bound heuristic is a constant so the upper bound cannot be reduced until a complete path to a goal state is found. For unweighted IBLAO*, this happens only short before a complete solution is found, which, consequently, is an optimal solution. Therefore, the performance for high error thresholds is almost the same as the performance for the lower thresholds.

Weighted IBLAO* avoids this, by first finding a suboptimal solution using the weighted heuristic and then gradually improving the solution. However, the many adjustments of the weight causes the weighted variant of IBLAO* to perform more backups, but this is counterweighted by the fewer number of expansions.

A constant upper bound is less problematic for the RTDP-based algorithms, because the trials are depth-first and therefore many, possibly suboptimal, paths to a goal state are found early. However, because of the many choices of actions, the trials become less efficient, since each path becomes less likely to be part of an optimal solution. Therefore, even though they make few backups, a much larger portion of the search space is explored.

Table 4.3: Comparison of algorithms on the problems from the rovers domain.

rover1	ϵ	V_{π_u}	*expansions*	*backups*	*time*
wIBLAO*	0.001	170.0	5	20	<0.010
IBLAO*	0.001	170.0	5	20	<0.010
ILAO*	0.001	170.0	5	16	<0.010
BRTDP	0.001	170.0	5	10	<0.010
FRTDP	0.001	170.0	5	20	<0.010
VPI-RTDP	0.001	170.0	5	10	<0.010
rover2	ϵ	V_{π_u}	*expansions*	*backups*	*time*
wIBLAO*	0.001	230.0	38	416	0.016
IBLAO*	0.001	230.0	30	156	0.016
ILAO*	0.001	230.0	59	497	0.016
BRTDP	0.001	230.0	64	168	0.016
FRTDP	0.001	230.0	57	208	0.016
VPI-RTDP	0.001	230.0	64	168	0.016
rover3	ϵ	V_{π_u}	*expansions*	*backups*	*time*
wIBLAO*	0.001	211.7	68	959	0.016
IBLAO*	0.001	211.7	59	341	0.016
ILAO*	0.001	211.7	146	1572	0.031
BRTDP	0.0010	211.7	183	500	0.031
FRTDP	0.001	211.7	173	608	0.031
VPI-RTDP	0.001	211.7	190	522	0.031
rover4	ϵ	V_{π_u}	*expansions*	*backups*	*time*
wIBLAO*	0.001	261.3	277	5380	0.078
IBLAO*	0.001	261.3	273	2055	0.047
ILAO*	0.001	261.3	697	10360	0.13
BRTDP	0.001	261.3	1199	3752	0.19
FRTDP	0.001	261.3	1105	3836	0.19
VPI-RTDP	0.001	261.3	1156	3638	0.19

Table 4.4: Comparison of algorithms on the problem *rover5* from the rovers domain.

rover5	ϵ	V_{π_u}	*expansions*	*backups*	*time*
wIBLAO*	0.1	609.4	13785	358106	7.0
	0.01	597.5	48744	2514690	29.6
	0.001	597.5	57387	3271515	36.4
IBLAO*	0.1	621.3	37362	549328	18.0
	0.01	599.4	61086	976507	29.9
	0.001	597.5	66628	1079763	32.8
ILAO*	0.1	609.4	40175	502817	17.2
	0.01	597.5	166227	3142255	71.2
	0.001	597.5	195892	4489816	83.1
BRTDP	0.1	613.8	92274	295412	35.3
	0.01	597.5	288137	1070994	109.0
	0.001	597.5	344766	1324538	121.3
FRTDP	0.1	615.9	90410	317096	36.3
	0.01	597.5	286655	1158646	121.1
	0.001	597.5	338432	1411122	135.4
VPI-RTDP	0.1	617.5	96444	317162	38.5
	0.01	597.5	286928	1080442	119.4
	0.001	597.5	340103	1322150	135.2

Table 4.5: Comparison of algorithms on the problem *rover6* from the rovers domain.

rover6	ϵ	V_{π_u}	*expansions*	*backups*	*time*
wIBLAO*	0.1	704.2	11532	313933	7.11
	0.01	686.7	33027	1672932	21.7
	0.001	686.7	38112	2225727	26.1
IBLAO*	0.1	735.0	33089	455971	17.3
	0.01	686.7	39773	567859	20.6
	0.001	686.7	47724	700254	24.7
ILAO*	0.1	693.3	23117	331570	11.2
	0.01	686.7	80666	1990941	37.0
	0.001	686.7	94863	2566326	44.4
BRTDP	0.1	693.3	43140	168840	16.9
	0.01	686.7	156051	769806	62.1
	0.001	686.7	177238	900978	71.3
FRTDP	0.1	703.3	54505	232704	21.5
	0.01	686.7	160857	842038	65.4
	0.001	686.7	180946	974982	74.7
VPI-RTDP	0.1	701.7	45111	182136	17.5
	0.01	686.7	148060	739986	59.0
	0.001	686.7	168699	868600	67.7

5 Case Study: Hydraulic Braking System

5.1 Introduction

This chapter presents a case study of the troubleshooting framework for a hydraulic braking system of a truck. This system is called a *retarder* and we will describe the system and how it can be modeled in the framework. The performance of the planning algorithm IBLAO* and the new heuristics is evaluated through empirical tests on the model.

5.2 The Retarder

The retarder is an auxiliary hydraulic braking system that allows braking of the truck without applying the conventional brakes. It consists of a mechanical system and a hydraulic system, and is controlled by an electronic control unit (ECU). The retarder generates braking torque by letting oil flow through a rotor driven by the vehicle's propeller axle causing friction. The kinetic energy is thereby converted into thermal energy in the oil that is cooled off by the cooling system of the truck. At full effect and high engine speed, the retarder can generate as much torque as the engine.

Figure 5.1 shows the retarder and how it is attached to the gearbox and Figure 5.2 shows a schematic of the retarder. The central component of the retarder is the torus which consists of two parts, a rotor (1) and a stator (2).

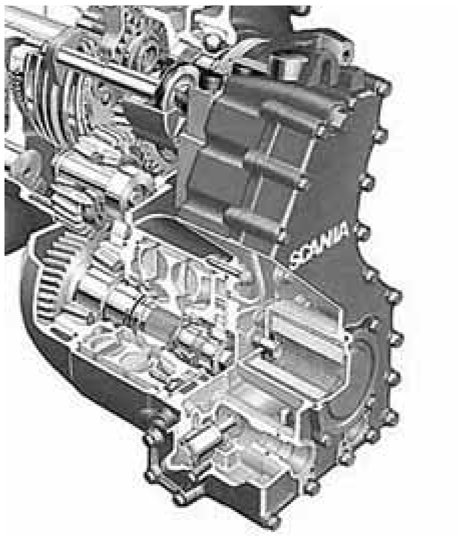


Figure 5.1: The retarder is an auxiliary braking system here shown attached to the gearbox.

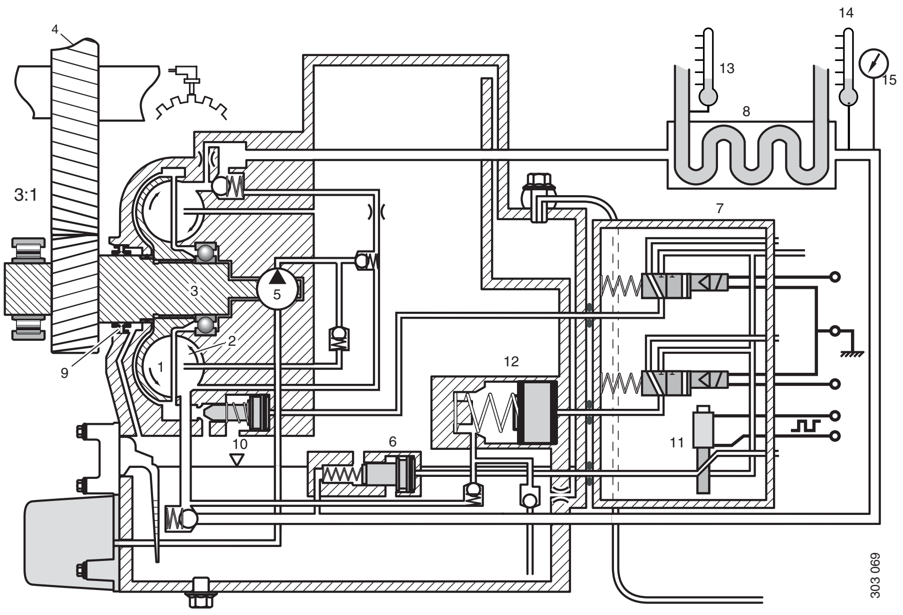


Figure 5.2: Schematic of the retarder

The rotor is connected to the retarder axle (3) and the stator is fixated to the retarder housing. By injecting oil into the torus, friction is created between the rotor and stator which is converted to braking torque on the propeller shaft (4) in the gear box. This friction heats up the oil which is circulated through a cooler (8) by the pump (5).

The amount of braking torque is proportional to the engine speed and the amount of oil in the system. When the retarder is engaged, oil is taken from the oil sump and inserted into the system through the accumulator valve (12). Smaller adjustments of the amount of oil in the system are made using the control valve (6). When the retarder is disengaged, the safety valve (10) is opened.

The valves are controlled by the ECU through a set of magnetic air valves (7) and a proportional valve (7). To control the system the ECU uses input from sensors that measure the coolant temperature (13), the oil temperature (14), and the oil pressure (15).

The retarder is representative for heavy vehicles because it consists of a combination of mechanical, hydraulic and electronic components.

5.3 The Model

We can create a diagnostic model for the retarder system that is an nsDBN as described in Section 3.5. The first time slice of the network is shown in Figure 5.3. The model has 20 persistent variables representing the components and it has 25 non-persistent variables representing the observations that can be made. The component variables are shown as filled circles and the observation variables are shown as white circles. Instant edges are shown as filled lines while non-instant edges are shown as dashed lines.

Component variables that have no parents may fail independently of each other. The CPT for such a component variable models the failure rate of that component. The CPT:s for the remaining variables are modeled with *leaky noisy-or* probability distributions [34]. Leaky noisy-or distributions can be used for causal Bayesian networks and for a variable with n parents, only $\mathcal{O}(n)$ parameters needs to be set to create a noisy-or CPT.

Let X be a two-valued stochastic variable where $\Omega_X = \{x_0, x_1\}$ and let $Y_1, \ldots, Y_n$ be the parents of X in the BN where $\Omega_{Y_i} = \{y_{i,0}, \ldots, y_{i,M_i}\}$ and $M_i = |\Omega_{Y_i}| - 1$. Then, in the leaky noisy-or distribution

$$P(X{=}x_1 | Y_1{=}y_{1,m_1}, \ldots, Y_n{=}y_{n,m_n}) = 1 - (1 - \theta_0) \prod_{i=1}^{n} q_i, \tag{5.1}$$

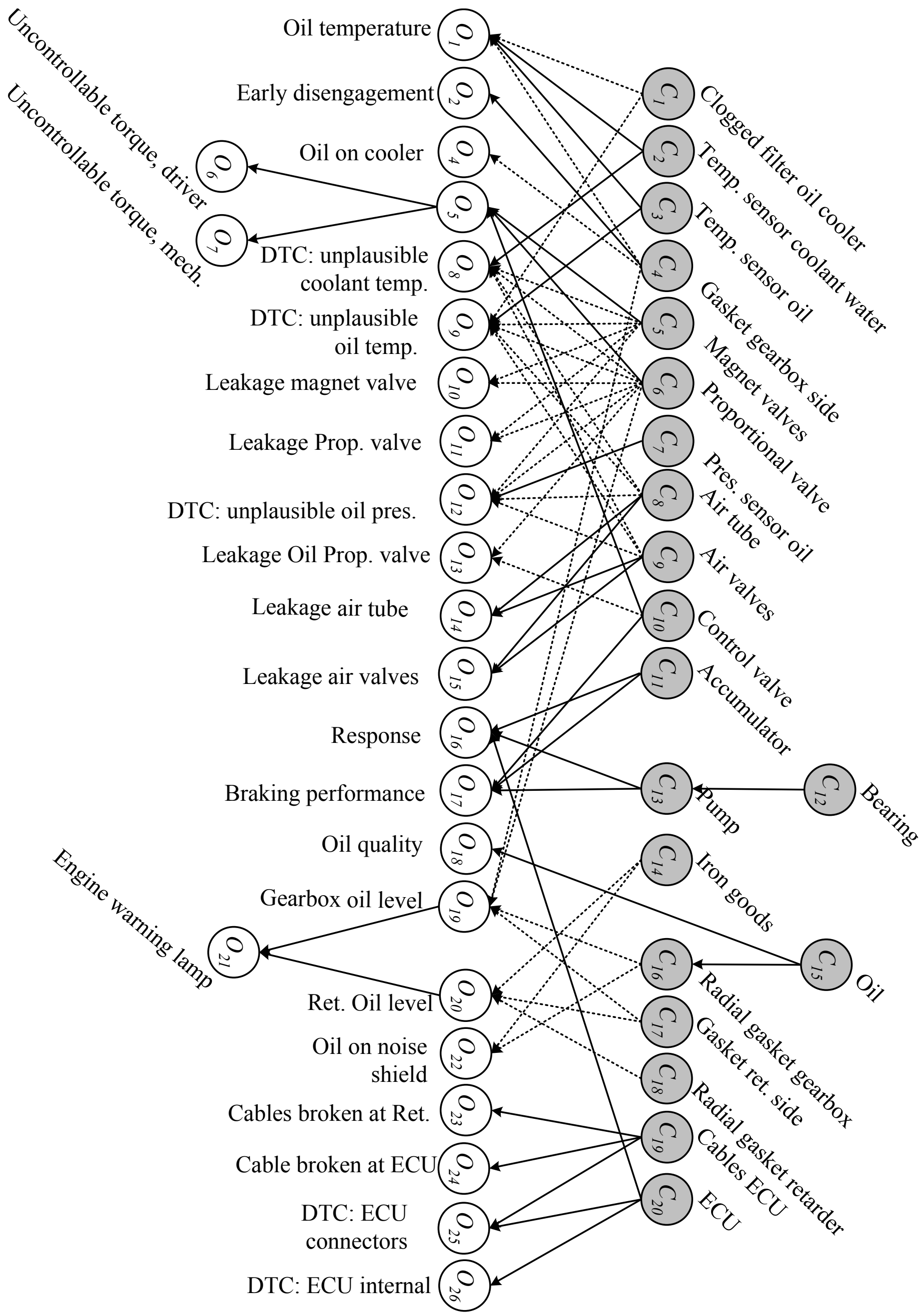


Figure 5.3: The nsDBN diagnostic model for the retarder.

where

$$q_i = \begin{cases} \frac{1-\theta_{i,m_i}}{1-\theta_0} & \text{if } m_i > 0, \\ 1 & \text{otherwise,} \end{cases}$$

and the parameters $\theta_0, \theta_{1,1}, \ldots, \theta_{n,M_n}$ are chosen so that $\theta_0 = P(X = x_1 | Y_1 = y_{i,0}, \ldots, Y_n = y_{n,0})$ and $\theta_{i,m} = P(X = x_1 | Y_1 = y_{i,0}, \ldots, Y_i = y_{i,m}, \ldots, Y_n = y_{n,0})$. The leaky noisy-or distribution should be interpreted as follows: Each variable Y_i may cause X to have the value x_i independently of the other parent variables when Y_i has the value y_{i,m_i} where $m_i > 0$. When each parent variable Y_i has the value $y_{i,0}$, θ_0 is the probability that $X = x_1$ due to some unknown cause other than Y_i.

For the modeling of the retarder, first all the components that are known to fail were identified and then for each such component, domain experts listed all observations that may occur because that component fails. Since leaky noisy-or distributions are used for the CPT:s, only one parameter needed to be set for each dependency and each fault mode of the components.

There are 68 actions available for the retarder and they are listed in Table 5.1. The effects and preconditions of all actions are obtained from the workshop manual [71]. The cost of each action is set to the sum of the costs of the resources consumed when the action is performed and the standard mechanic wage times the *standard time* for that action, i.e. the amount of time it takes to perform the action in normal work pace.

Of these 68 actions, 20 have a repair effect, 23 have observe effects, and 26 have effects that assemble or disassemble parts of the vehicle that are modeled with feature variables.

The features that were necessary to model were obtained from the workshop manual and the assembly graph for the retarder shown in Figure 5.4 shows how the 13 features depend on each other. The feature variables F_4, F_7–F_{13} represent parts of the retarder that can be disassembled or removed. The other features are not as intuitive. The top node F_1 represents whether the vehicle is inside the workshop or not. The vehicle must be outside when the vehicle is test driven and when troubleshooting is ended. The feature variable F_2 represents whether the cab of the truck is tilted or not and F_3 represents whether safety supports for the vehicle frame are in place or not which is a requirement when actions under the vehicle are performed. The feature variables F_5–F_8 represents different fluids that can be drained.

There are 10 observation variables that do not have an action that observes them. These are Diagnostic Trouble Codes (DTC:s) and observations that the driver can make. The values of these observations are given to the troubleshooter when troubleshooting starts.

Table 5.1: All available actions for the retarder

a_0	Stop	a_{34}	Check for air leakage
a_1	Replace oil filter	a_{35}	Check oil quality
a_2	Replace temp. sensor, coolant	a_{36}	Check oil level, retarder
a_3	Replace temp. sensor, oil	a_{37}	Check oil level, gearbox
a_4	Replace gasket, gearbox side	a_{38}	Check ECU cables, retarder side
a_5	Replace magnet valves	a_{39}	Check ECU cables, ECU side
a_6	Replace proportional valve	a_{40}	Check retarder performance
a_7	Replace pressure sensor, oil	a_{41}	Drive in vehicle
a_8	Replace air tube	a_{42}	Drive out vehicle
a_9	Replace air valves	a_{43}	Tilt cab
a_{10}	Replace control valve	a_{44}	Close cab
a_{11}	Replace accumulator	a_{45}	Fit frame support
a_{12}	Replace bearing	a_{46}	Remove frame support
a_{13}	Replace pump	a_{47}	Remove noise shield
a_{14}	Replace iron goods	a_{48}	Fit noise shield
a_{15}	Replace radial gasket, retarder	a_{49}	Drain retarder oil
a_{16}	Replace gasket, retarder side	a_{50}	Fill retarder oil
a_{17}	Replace radial gasket, gearbox	a_{51}	Drain coolant
a_{18}	Replace cables, ECU	a_{52}	Fill coolant
a_{19}	Replace ECU	a_{53}	Drain gearbox oil
a_{20}	Inspect temp. sensor coolant	a_{54}	Fill gearbox oil
a_{21}	Inspect temp. sensor oil	a_{55}	Remove proportional valve
a_{22}	Inspect gasket, gearbox side	a_{56}	Fit proportional valve
a_{23}	Inspect pressure sensor oil	a_{57}	Remove propeller shaft
a_{24}	Inspect bearing	a_{58}	Fit propeller shaft
a_{25}	Inspect pump	a_{59}	Remove oil cooler
a_{26}	Inspect iron goods	a_{60}	Fit propeller shaft
a_{27}	Inspect radial gasket, retarder	a_{61}	Remove retarder
a_{28}	Inspect gasket, retarder side	a_{62}	Fit retarder
a_{29}	Inspect radial gasket, gearbox	a_{63}	Disassemble retarder housing
a_{30}	Check for oil on cooler	a_{64}	Assemble retarder housing
a_{31}	Check for leakage, magn. valves	a_{65}	Remove retarder axle
a_{32}	Check for leakage, prop. valve	a_{66}	Fit retarder axle
a_{33}	Check for leakage, control valve	a_{67}	Test drive

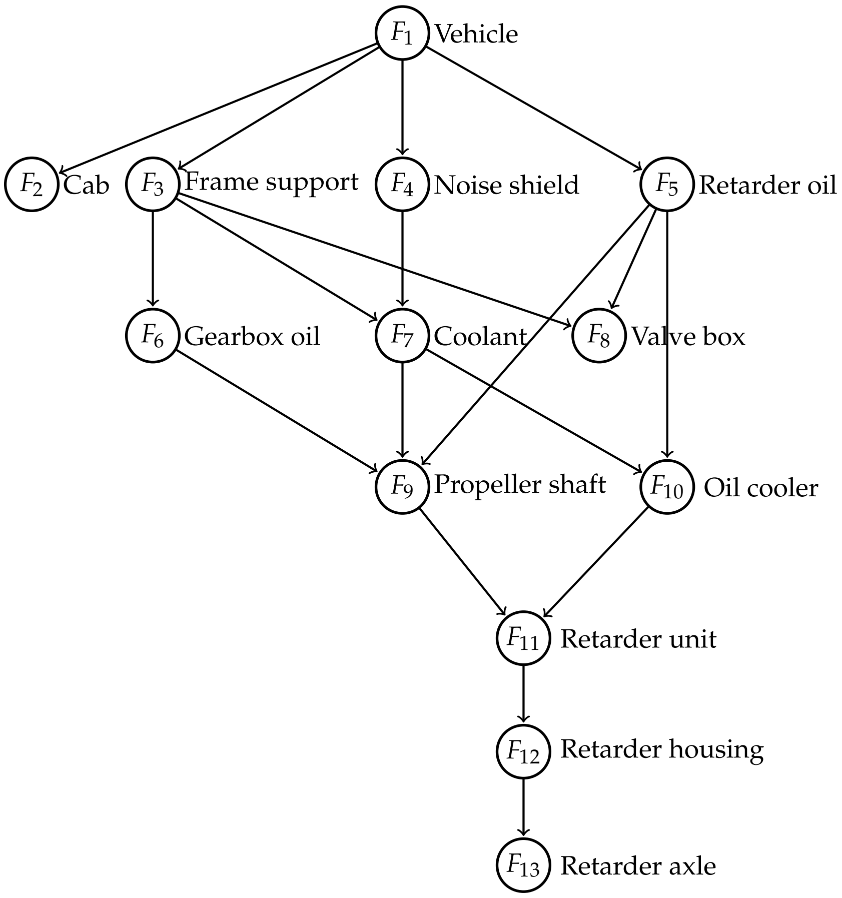


Figure 5.4: The assembly graph for the retarder.

All details and parameters for the retarder model can be seen in the retarder model file shown in Appendix C.

5.4 Evaluation

5.4.1 The Problem Set

There are 10 initial observations that can be made. All of these observations are binary which means that a troubleshooting session may start in one of 1024 initial states. However, many of these are either highly improbable or impossible. Given that some component is faulty, the 56 most likely combinations of initial observations represent 99% of the probability mass. These 56 initial

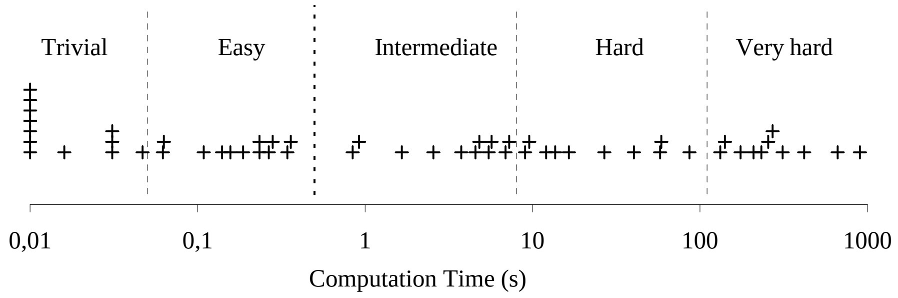


Figure 5.5: The partition of the problems into classes, trivial, easy, intermediate, hard, and very hard.

states will be our problem set.

Plans for each of the 56 problems are found using Iterative Bounding LAO* with the following settings: the lower bound heuristic h_{comb}, the upper bound heuristic h_{fixed}, the parameter $\alpha = 0.9$, and the weight function $w = \sqrt{1 + \hat{\epsilon}}$. Planning is halted when a troubleshooting plan is found that can be proved to have a relative error bound smaller than 0.001 or when it runs out of memory. If the error bound is smaller than 0.001 when the algorithm is halted, the problem is considered to be solved. The relative error bound, upper bound, number of state expansions, number of state backups, and total computation time is recorded for each problem. The problems were sorted by the time it took to find a plan and grouped into 5 different problem classes of roughly equal size: 12 *trivial* problems that were all solved in less than 0.05 seconds, 12 *easy* problems that were all solved in less than 0.5 second, 11 *intermediate* problems that were all solved in less than 8 seconds, 10 *hard* problems that were all solved in less than 2 minutes, and 11 *very hard* problems that required more than 2 minutes to solve. Two problems in the very hard problem class were not completely solved because the planner ran out of memory. When this happened, the error bounds on the expected cost of repair were 0.012 and 0.10 respectively. Figure 5.5 shows how the problems are partitioned by computation time.

Table 5.2 shows the averages of the relative error bounds, number of expansions, number of backups, and computation time over the problems in each problem class. This will be used as a baseline for further evaluations. The troubleshooting framework has been implemented in Java and all experiments except those in Section 5.4.4 are run on a 2.40 GHz Intel Core2 Duo P8600 CPU where the Java Virtual machine was allowed a maximum heap size of 1600 MB.

Table 5.2: Average results for troubleshooting with Iterative Bounding LAO* using optimal settings.

Problem class	Error bound	Expansions	Backups	Comp. time (s)
Trivial	0.0003	18.0	215.2	0.01
Easy	0.0009	166.6	2955.5	0.20
Intermediate	0.0009	1371.5	45414.5	4.04
Hard	0.0009	8211.1	343506.1	33.08
Very hard	0.0116	47849.9	3037271.9	337.42

The comparison in Section 5.4.4 is done on a 2.67 GHz Intel Core2 Quad Q6600 CPU where the Java Virtual machine was allowed a maximum heap size of 5 GB.

5.4.2 Weighted IBLAO* vs. IBLAO*

In this section we study how IBLAO* behaves when a weight function is used compared to when it is not. The upper and lower bounds are recorded over time for Iterative Bounding LAO* using the weight function $w = \sqrt{1+\hat{\epsilon}}$ (wIBLAO*) and Iterative Bounding LAO* using no weights, $w = 0$ (IBLAO*). The algorithms are halted when either the relative error bound becomes smaller than 0.001 or they run out of memory. Figures 5.6–5.7 shows five plots of how the average upper and lower bounds converge over time for each problem class. On the value axis, the bounds at each time point are normalized with the converged value of the upper bound. This value is our best estimate of the optimal ECR, so the value axis shows the bounds' relative difference from the optimal ECR. The bounds for wIBLAO* are shown with solid lines and for IBLAO* they are shown with dashed lines.

The upper bound value for wIBLAO* converges significantly faster while for IBLAO* the convergence of the lower bound is slightly faster. Compared to IBLAO*, when the weight is high, wIBLAO* commits more to suboptimal solutions and will explore these further before the weight is reduced and other potentially optimal solutions are explored. Note that for the harder problems, the upper bound quickly converges to a value within a few percent of optimal while the lower bound converges much slower. This means that a high quality decision can be made long before it can be proven to have that quality, since Iterative Bounding LAO* uses the upper bound to create the policy that is returned, while the lower bound is used only to prove how close to optimal that policy is.

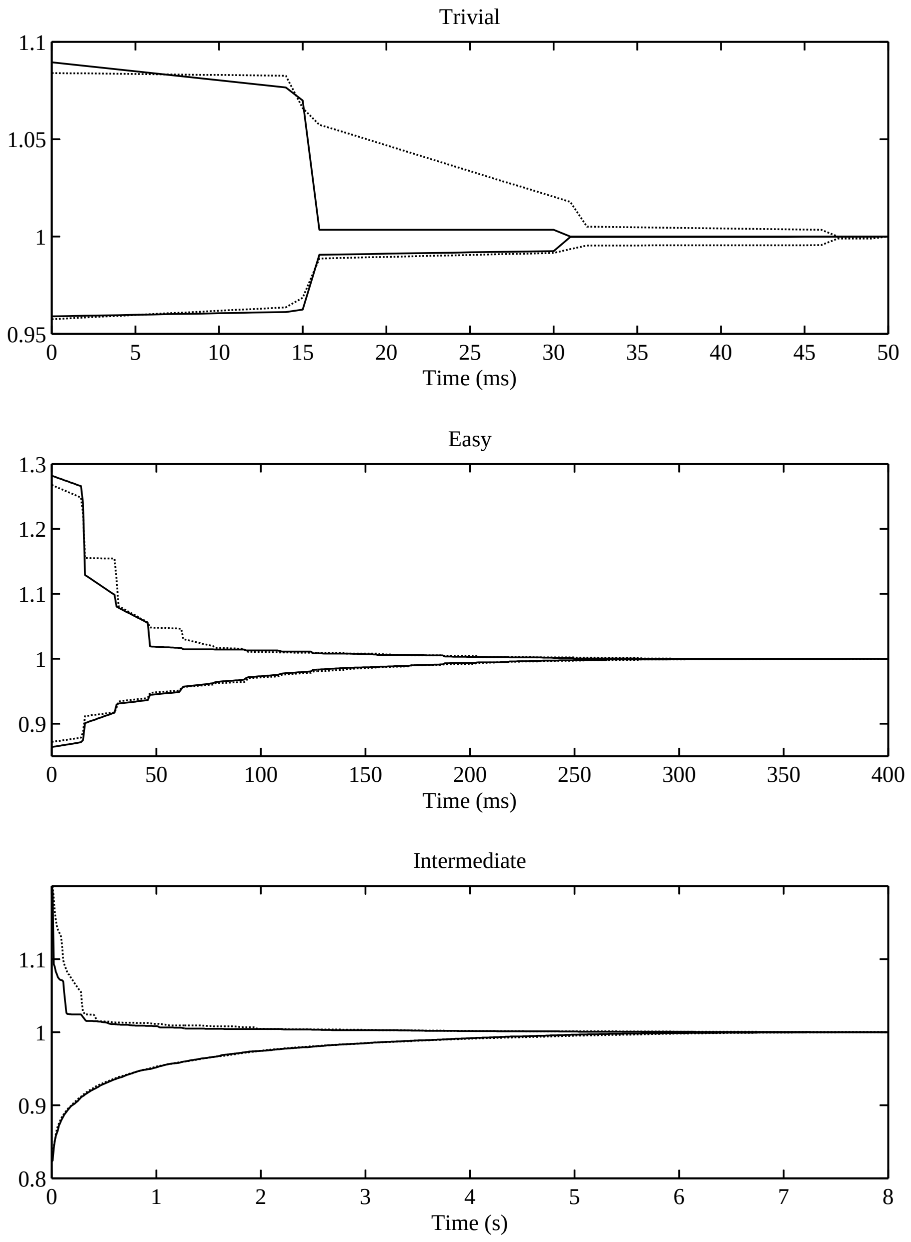


Figure 5.6: Convergence of the average upper and lower bounds using wIBLAO* (solid line) and IBLAO* (dashed line).

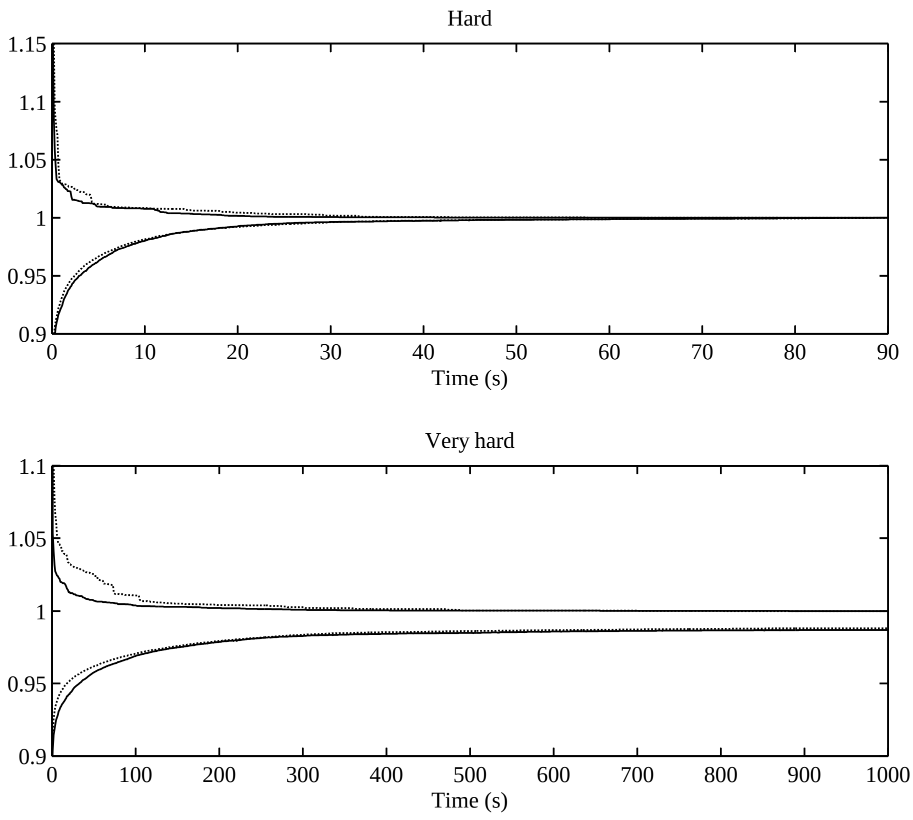


Figure 5.7: Convergence of the average upper and lower bounds using wIBLAO* (solid line) and IBLAO* (dashed line).

5.4.3 Lower Bound Heuristics

The lower bound heuristic affects how many states must be expanded to prove that a troubleshooting plan has a certain quality. We have compared weighted Iterative Bounding LAO* using three different lower bound heuristic functions: h_{comb}, h_{fo}, and h_{ent}.

Table 5.3 shows for each heuristic function and for each problem class, how many percent of the problems that were solved and the average of the error bounds when the algorithm was halted.

Table 5.4 shows for each heuristic function and for each problem class, the average number of expansions, the average number of backups, and the average computation time in seconds. The averages in Table 5.4 are taken only over the problems that were solved using both h_{comb} and h_{fo}. No values are shown for h_{ent} for the problem classes intermediate, hard, and very hard because not all problems, that were solved using h_{comb} and h_{fo}, were solved using h_{ent}.

The results shows that the h_{comb} heuristic is a tremendous improvement over the heuristic h_{ent} and that it is only slightly but consistently better than h_{fo}. This is because many information-gaining actions in the retarder model have much smaller cost than most repair actions. This causes the contribution from the entropy in h_{comb} to become low. This is also the reason why the h_{ent} heuristic becomes so relatively ineffective.

5.4.4 Comparison with Other Algorithms

In this section, IBLAO* is compared to the other algorithms for solving SSPP:s used in the comparisons in Section 4.2: FRTDP, BRTDP, VPI-RTDP, and ILAO*. We will expect all of these algorithms to perform worse than Iterative Bounding LAO* because for the troubleshooting problem, state expansions are expensive and not very cyclic.

The algorithms are implemented and parameterized in the same way as for the comparisons in Section 4.2. As before, the algorithms are halted when the algorithm runs out of memory or when a problem is solved, i.e. a solution that is proven to have an error bound lower than 0.001 is found. To obtain, a higher success rate, the algorithms are allowed 5 GB of memory instead of 1600 MB.

Table 5.5 shows for each algorithm and for each problem class, how many percent of the problems that were solved and the average of the error bounds when the algorithms were halted.

Table 5.6 shows for each algorithm and for each problem class, the average number of expansions, the average number of backups, and the average computation time in seconds. The averages in Table 5.6 are taken only over

Table 5.3: Percentage of the problems that were solved and the average of the error bounds when the algorithm was halted for weighted Iterative Bounding LAO* using different lower bound heuristics.

Heuristic	Problem class	Solved (%)	Error bound
h_{comb}	Trivial	100.0	0.0003
	Easy	100.0	0.0009
	Intermediate	100.0	0.0009
	Hard	100.0	0.0009
	Very hard	81.8	0.0116
h_{fo}	Trivial	100.0	0.0003
	Easy	100.0	0.0009
	Intermediate	100.0	0.0009
	Hard	100.0	0.0010
	Very hard	81.8	0.0128
h_{ent}	Trivial	100.0	0.0007
	Easy	100.0	0.0010
	Intermediate	9.1	0.7431
	Hard	0.0	4.5195
	Very hard	0.0	9.8214

Table 5.4: The average number of expansions, the average number of backups, and the average computation time in seconds or weighted Iterative Bounding LAO* using different lower bound heuristics.

Algorithm	Problem class	Expan-sions	Backups	Comp. time (s)	No. of problems
h_{comb}	Trivial	18.0	215.2	0.01	12/12
	Easy	166.6	2955.5	0.20	12/12
	Intermed.	1371.5	45414.5	4.04	11/11
	Hard	8211.1	343506.1	33.08	10/10
	Very hard	42151.6	2850716.2	238.49	9/11
h_{fo}	Trivial	18.8	229.0	0.02	12/12
	Easy	174.4	3191.1	0.23	12/12
	Intermed.	1508.5	50377.4	4.82	11/11
	Hard	8761.1	367878.8	37.69	10/10
	Very hard	44611.2	2916254.4	269.29	9/11
h_{ent}	Trivial	1085.0	169837.8	1.56	12/12
	Easy	16569.6	3200774.3	37.94	12/12

the problems that were solved with all algorithms. No values are shown for the very hard problem class because none of the other algorithms were able to solve a single problem in that problem class.

The results show a significant difference in performance between Iterative Bounding LAO* and the other algorithms. As for the problems from the Rovers domain described in Section 4.2.2, the deep trials of the RTDP-based algorithms are inefficient for the troubleshooting problems. The RTDP-based algorithms explore deep into areas of the search space that can be proven to be suboptimal through a more shallow search. ILAO* expands creates a complete policy before it backs up and therefore it may also search in suboptimal areas of the search space longer than necessary.

5.4.5 Composite Actions

In this section we will study how much more difficult the planning problem would be if we did not consider composite actions. When composite actions are not used the total search space becomes much larger and we can expect the planner to have difficulties with the harder problems. This is confirmed by the result shown in Table 5.7.

5.4.6 Relaxing the Assumptions

In Section 3.7 it is discussed how some of the assumptions made in Section 3.4 can be relaxed. When Assumption 1 is relaxed we can use loss functions, but then we must use different lower bound heuristics. However, the troubleshooting problem becomes easier to solve since components that are suspected to be faulty with only a very small probability can safely be disregarded. The loss function that we will use assigns a penalty of 10000 for each faulty component that is not repaired. Table 5.8 shows the results for the problems when loss functions are used and when they are not where the upper bound of the expected cost of repair is also recorded. We can see that the problems are solved faster when loss functions are used and that the expected cost of repair is lower.

When repairs may fail and it is not possible to verify the function of the system, the problem becomes more difficult. However, using the heuristics $\hat{h}_{fo}$ and $\hat{h}_{fixed}$ described in Section 3.7 many problems can be solved in reasonable time. Table 5.9 shows the results for the following cases: repairs never fail and function control is possible, repairs never fail and function control is not possible, repairs fail with probability 0.001 and function control is possible, and repairs fail with probability 0.001 and function control is not possible.

Adding the possibility of failed repairs and removing the possibility of a function control makes the troubleshooting problem more difficult and the

Table 5.5: Percentage of the problems that were solved and the average of the error bounds when the algorithms were halted for the different planning algorithms.

Algorithm	Problem class	Solved (%)	Error bound
wIBLAO*	Trivial	100.0	0.0004
	Easy	100.0	0.0009
	Intermediate	100.0	0.0009
	Hard	100.0	0.0010
	Very hard	81.8	0.0124
FRTDP	Trivial	100.0	0.0003
	Easy	100.0	0.0008
	Intermediate	100.0	0.0009
	Hard	50.0	0.0091
	Very hard	0.0	0.0680
BRTDP	Trivial	100.0	0.0004
	Easy	100.0	0.0008
	Intermediate	100.0	0.0010
	Hard	40.0	0.0170
	Very hard	0.0	0.0782
VPI-RTDP	Trivial	100.0	0.0003
	Easy	100.0	0.0008
	Intermediate	100.0	0.0010
	Hard	40.0	0.0178
	Very hard	0.0	0.0681
ILAO*	Trivial	100.0	0.0001
	Easy	100.0	0.0006
	Intermediate	81.8	0.0025
	Hard	0.0	0.0538
	Very hard	0.0	0.2566

Table 5.6: The average number of expansions, the average number of backups, and the average computation time in seconds for the different planning algorithms.

Algorithm	Problem class	Expan-sions	Backups	Comp. time (s)	No. of problems
wIBLAO*	Trivial	17.8	217.3	0.02	12/12
	Easy	166.4	3191.9	0.26	12/12
	Intermed.	1291.4	44235.4	5.08	9/11
	Hard	3241.7	123996.3	16.06	3/10
FRTDP	Trivial	30.9	168.3	0.02	12/12
	Easy	646.7	3089.8	0.53	12/12
	Intermed.	30989.9	103930.9	41.63	9/11
	Hard	83576.7	244798.0	125.60	3/10
BRTDP	Trivial	421.6	2903.2	0.19	12/12
	Easy	7398.0	43186.8	4.18	12/12
	Intermed.	58501.7	221979.1	65.99	9/11
	Hard	131694.3	478653.3	161.61	3/10
VPI-RTDP	Trivial	608.2	6303.2	0.21	12/12
	Easy	9528.3	55563.5	4.08	12/12
	Intermed.	56332.6	213578.7	64.50	9/11
	Hard	145276.3	582009.3	165.08	3/10
ILAO*	Trivial	71.6	808.3	0.06	12/12
	Easy	4114.2	57218.3	4.44	12/12
	Intermed.	72496.3	1573655.1	93.95	9/11
	Hard	131622.7	2938452.0	167.4	3/10

Table 5.7: Average results for troubleshooting using wIBLAO* when composite actions are used and when they are not.

Comp. actions	Problem class	Error bound	Expan- sions	Backups	Comp. time (s)	Solv- ed (%)
Yes	Trivial	0.0003	18.0	215.2	0.01	100.0
	Easy	0.0009	166.6	2955.5	0.20	100.0
	Intermed.	0.0009	1371.5	45414.5	4.04	100.0
	Hard	0.0009	8211.1	343506.1	33.08	100.0
	Very hard	0.0116	47849.9	3037271.9	337.42	81.8
No	Trivial	0.0004	323.2	14677.9	0.38	100.0
	Easy	0.0009	2909.8	203435.7	5.14	100.0
	Intermed.	0.0010	30913.5	3908583.4	120.30	100.0
	Hard	0.0010	109820.2	13864854.9	541.70	100.0
	Very hard	0.0286	226209.9	22341824.3	1620.42	9.1

Table 5.8: Average results for troubleshooting when a loss function is used and when they are not.

Loss functions	Problem class	Error bound	Expan- sions	Upper bound	Comp. time (s)
No	Trivial	0.0003	18.0	1098.2	0.01
	Easy	0.0009	166.6	1147.2	0.20
	Intermed.	0.0009	1371.5	1342.9	4.04
	Hard	0.0009	8211.1	1559.3	33.08
	Very hard	0.0116	47849.9	1848.3	337.42
Yes	Trivial	0.0002	9.8	1058.6	0.01
	Easy	0.0008	96.9	1094.3	0.13
	Intermediate	0.0009	755.8	1302.5	2.17
	Hard	0.0009	3667.0	1522.7	15.62
	Very hard	0.0108	19156.3	1806.1	161.10

Table 5.9: Average results for troubleshooting when repair actions may fail and function control is not available.

Failing repairs	Function control	Problem class	Error bound	Expansions	Upper bound	Comp. time (s)
No	Yes	Trivial	0.0002	8.7	1058.6	0.01
		Easy	0.0008	99.2	1094.2	0.17
		Intermed.	0.0009	771.4	1302.5	2.73
		Hard	0.0010	3396.2	1522.7	19.18
		Very hard	0.0128	22854.1	1810.5	279.73
No	No	Trivial	0.0002	8.8	1058.6	0.01
		Easy	0.0007	104.3	1097.5	0.16
		Intermed.	0.0009	942.1	1311.2	3.17
		Hard	0.0010	4367.0	1527.8	22.58
		Very hard	0.0127	24477.1	1813.2	286.16
Yes	Yes	Trivial	0.0003	21.8	1071.6	0.03
		Easy	0.0009	164.8	1105.6	0.44
		Intermed.	0.0009	1312.3	1320.2	6.76
		Hard	0.0010	7429.3	1542.3	101.58
		Very hard	0.0147	36314.9	1826.96	767.34
Yes	No	Trivial	0.0003	23.1	1071.6	0.05
		Easy	0.0008	169.1	1110.0	0.65
		Intermed.	0.0009	1544.7	1331.3	12.06
		Hard	0.0010	8707.7	1548.6	158.23
		Very hard	0.0165	38886.5	1833.9	832.97

expected cost of repair becomes higher. The problem becomes only slightly more difficult to solve when there is no possibility of making a function control, but when repairs may fail the problem becomes much more difficult to solve. This is because every repair action introduces may introduce new faults that have to be treated and the search space becomes larger. For the same model, the performance of the planner is slightly reduced when the heuristic $\hat{h}_{\mathit{fixed}}$ is used instead of h_{fixed}.

5.4.7 Troubleshooting Performance with Limited Decision Time

In this section we will compare troubleshooting using IBLAO* when the time allowed to make decisions is limited with the greedy look-ahead approaches used in Sun and Weld [79] and Langseth and Jensen [42], and with the other planning algorithms.

Comparison with Look-Ahead Search

In Sun and Weld [79], the estimated remaining ECR in a state s, $\widehat{ECR}_{Sun}(s)$, is the sum of the cost of repairing all components if the true diagnosis is known plus the entropy weighted with the average observe action cost, i.e.

$$\widehat{ECR}_{Sun}(s) = h_{fo}(s) + h_{ent}(s).$$

where for the computation of $h_{ent}(s)$, the average cost of the composite actions with observe effects is used instead of the minimum action cost. The selected action a^*_{Sun} is then

$$a^*_{Sun}(s) = \arg\min_{a \in \mathcal{A}'(s)} T_a \widehat{ECR}_{Sun}(s)$$

where $\mathcal{A}'(s)$ is the set of possible composite actions applicable in s.

In Langseth and Jensen [42] the ECR is estimated using the heuristic given by (3.44) from Heckerman et al. [33]. This heuristic does not apply when actions have preconditions and multiple components can be faulty at the same time. Therefore we will use the heuristic h_{fixed} instead. Let a' be the first action in the fixed strategy used to derive h_{fixed}. If

$$c(a',s) + \sum_{s' \in succ(a',s)} p(s',s,a') \min_{a \in \mathcal{A}'(s')} T_a h_{\mathit{fixed}}(s') \le \arg\min_{a \in \mathcal{A}'(s)} T_a h_{\mathit{fixed}}(s)$$

the selected action a^*_{Lang} is a' otherwise

$$a^*_{Lang}(s) = \arg\min_{a \in \mathcal{A}'(s)} T_a h_{\mathit{fixed}}(s)$$

Table 5.10: Average expected cost of repairs for troubleshooting when decision time is limited. $\underline{ECR}^*$ and $\overline{ECR}^*$ shows the best known lower and upper bounds of the optimal expected cost of repair.

	Trivial	Easy	Inter-mediate	Hard	Very hard
$\overline{ECR}^*$	1098.0	1146.8	1342.5	1559.0	1846.1
$\underline{ECR}^*$	1097.9	1146.5	1341.7	1557.8	1822.4
ECR_{Sun}	1189.4	1296.2	1734.2	2176.2	2949.8
ECR_{Lang}	1125.2	1178.6	1381.9	1626.4	1908.0
ECR_1	1098.0	1146.8	1342.7	1561.3	1854.1
ECR_{10}	1098.0	1146.8	1342.5	1559.0	1846.6

where $\mathcal{A}'(s)$ is the set of possible composite actions applicable in s. This means that search space is explored one step for all actions except a' where it is explored two steps.

To evaluate these look-ahead methods against the planning based method presented in this thesis, we will study the expected cost of repair for each method i and each problem in the problem set, where the expected cost of repair is computed as:

$$ECR_i(s) = c(a_i^*(s), s) + \sum_{s' \in succ(a_i^*, s)} p(s', s, a_i^*) ECR_i(s').$$

where the decision $a_i^*(s)$ is computed for all reachable states s using the method i. The value $ECR_i(s_0)$ is the *actual* expected cost of repair when the decisions are made using method i.

By varying the time the planner can use to make a decision, we can evaluate the advantage of planning. The expected cost of repair is computed when weighted IBLAO* aborts planning after a fixed time. The expected cost ECR_1 is for 1 second of planning time and ECR_{10} is for 10 seconds of planning time. The results are shown in Table 5.10.

The greedy selection strategy used in Sun and Weld [79] performs the worst. This is because their cost function often underestimates the minimal ECR. Underestimating the minimal ECR when actions are selected greedily can cause the selected action to be an action with low cost and little effect on the state and thereby move expensive but inevitable actions beyond the planning horizon. On the other hand, the selection strategy used in Langseth and Jensen [42] performs remarkably well together with the h_{fixed} heuristic. This is because the value h_{fixed} is an admissible upper bound that corresponds to an executable troubleshooting plan. Other actions will only be selected if they improve the upper bound within the planning horizon.

Table 5.11: A comparison of the average expected cost of repairs for troubleshooting when planning time is limited using different planning algorithms. $\underline{ECR}^*$ and $\overline{ECR}^*$ shows the best known lower and upper bounds of the optimal expected cost of repair.

	Trivial	Easy	Inter-mediate	Hard	Very hard
$\overline{ECR}^*$	1098.0	1146.8	1342.5	1559.0	1846.1
$\underline{ECR}^*$	1097.9	1146.5	1341.7	1557.8	1822.4
wIBLAO* 1 s	1098.0	1146.8	1342.7	1561.3	1854.1
FRTDP 1 s	1098.0	1146.8	1343.5	1564.2	1854.6
BRTDP 1 s	1100.4	1146.9	1353.8	1607.8	1870.8
VPI-RTDP 1 s	1100.4	1148.3	1348.5	1615.4	1874.6
ILAO* 1 s	1098.0	1146.9	1351.9	1623.6	1883.8
wIBLAO* 10 s	1098.0	1146.8	1342.5	1559.0	1846.6
FRTDP 10 s	1098.0	1146.8	1343.4	1561.4	1850.8
BRTDP 10 s	1098.0	1146.8	1342.7	1606.5	1860.6
VPI-RTDP 10 s	1098.0	1146.8	1342.7	1603.8	1874.0
ILAO* 10 s	1098.0	1146.8	1343.0	1604.6	1878.5

Not surprisingly, the selection strategy based on planning performs the best. However, even with a short time limit of 1 second, the performance is within 0.5% of the best known upper bound of the optimal ECR. After a time limit of 10 seconds, performance is at most 0.03% from the upper bound of the optimal ECR.

When compared with ECR_{Lang}, the improvement could seem to be marginal. However, the improvement is consistent. For all problems in the problem sets, the selection of actions using planning yielded an ECR equal to or less than for the greedy selection strategies. Also, a reduction of the ECR saves money and reducing the ECR with only a few percent can lead to a great increase in marginal profit for both the workshop and the vehicle owner.

Comparison with Other Planning Algorithms

In Section 5.4.4 we saw that wIBLAO* produced troubleshooting plans with better quality than when the other state-of-the-art algorithms were used. It could be the case that some of these algorithms make better decisions than wIBLAO* even though the error bound of the plan is worse. In this section we will evaluate this by comparing all algorithms when 1 and 10 seconds of planning time is allowed.

The results are shown in Table 5.11 and weighted Iterative Bounding LAO* still has the best average performance for all problem sets.

Different Upper Bound Heuristic Function

When a constant upper bound heuristic, $h_{const}(s) = 10000$ for all non-goal states s, is used instead of the h_{fixed} heuristic, the performance degrades for the intermediate, hard, and very hard problems (1346.9, 1565.6, and 1932.7 for h_{const} versus 1342.7, 1561.3, and 1854.1 for h_{fixed} after 1 second of planning time). This upper bound grossly overestimates the optimal expected cost and therefore the algorithm needs to explore every policy deeper to make a better decision than when the heuristic h_{fixed} is used. With only one second of planning there is not enough time for this on the more difficult problems.

6 Conclusion

This thesis presents a framework for computer-assisted troubleshooting that can for example be used to help a mechanic find and repair faults on a damaged truck. The framework consists of two major components. The first component is the Planner that tries to find a plan of actions that repairs all faults on the system. The Planner uses the second component, the Diagnoser, which, given the knowledge of previously made observations and performed actions, can compute a probability distribution over possible diagnoses and the probability that the next action will have a certain outcome. The decision that is recommended to the user of the computer-assisted troubleshooting system is the first action of the plan created by the Planner. Emphasis is placed on solving the decision problem better than can be done with existing methods so that a good trade-off between computation time and solution quality can be made.

We have shown how a Diagnoser can be made that uses non-stationary dynamic Bayesian networks (nsDBN:s) to model the system. The framework of nsDBN:s for troubleshooting [56] supports many events that are relevant for troubleshooting heavy vehicles: observations, repairs, and the operation of the system. In this thesis we show how we can convert the nsDBN into a static two-layer Bayesian network that can be used instead of the explicit nsDBN to answer the queries needed by the Diagnoser in the framework.

The main contributions of this thesis are the new planning algorithm Iterative Bounding LAO* (IBLAO*) and the improved search heuristics. IBLAO* is a new efficient general anytime search algorithm for ϵ-optimal solving of problems formulated as Stochastic Shortest Path Problems. In the case study, we saw that IBLAO* finds troubleshooting plans with higher quality than the other state-of-the-art planning algorithms in less time. We also saw that the new heuristics improves the speed with which high quality solutions can be found.

When compared to previous methods for troubleshooting that are based on look-ahead search, the expected cost of repair is already consistently improved when decisions are made after only 1 second of planning time using the troubleshooting framework presented in this thesis. When 10 seconds of planning time is allowed, the performance is within 0.1% for the tested cases. In the automotive industry it is important to reduce the repair and maintenance costs. Any improvement in the expected cost of repair can yield great savings for the service workshops and vehicle owners.

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A

Notation

$\mathbb{1}$	An indicator function.
α	The decrease factor in Iterative Bounding LAO*.
γ	The discount factor for an MDP policy, or a function for determining the statuses of the component variables after a set of repair events.
ϵ	The relative error, or
ϵ^t	An effect that occurred at time t.
$\hat{\epsilon}$	Upper bound of the relative error.
$\bar{\epsilon}$	The current error threshold in Iterative Bounding LAO*.
$\boldsymbol{\epsilon}^{1:t}$	A sequence of effects that occurred between time 1 and t.
η	A normalizing function for probability distributions.
θ	A parameter of a Bayesian network.
Θ	A set parameters of a Bayesian network.
π	A troubleshooting plan, or an MDP policy.
π_l	A lower bound policy.
π_u	A upper bound policy.
π^*	An optimal troubleshooting plan, or an optimal MDP policy.
τ	The duration of an operation event, or a function for computing the next belief state in POMDP:s.
Υ	Set of constraints on the belief state space.

Φ	The fringe states of a search graph.
ω	An operation event, or a function for computing observation probabilities in POMDP:s
Ω	Outcome space.
a	An action.
a^*	An optimal action.
A	The assembled mode of a feature variable.
$\mathcal{A}$	A set of actions.
b	A belief state.
b_ω	A belief state describing the state at the time of the last operation event.
$\mathcal{B}$	A belief state space.
B	A Bayesian network.
B_{ns}	A non-stationary dynamic Bayesian network.
B^t	Time slice t of the dynamic Bayesian network B.
$\mathcal{B}$	A set of belief states.
c	A fault mode of the component variable C, or a cost function.
c_a	The cost of the action a.
$\mathbf{c}$	An assignment of the fault modes of the component variables $\mathbf{C}$.
C	A component variable.
$\mathbf{C}$	A set of component variables.
D	The disassembled mode of a feature variable.
e	An event.
e^t	An event that occurred at time t.
$\mathbf{e}$	A sequence of events.
$\mathbf{e}^{1:t}$	The sequence of events that occurred between time 1 and t.
$\mathcal{E}$	A set of sequences of events, the effects of an action, or the set of edges of a graph.
f	A feature mode of the feature variable C, or an evaluation function.
f_l	A lower bound evaluation function.
f_u	An upper bound evaluation function.
$\mathbf{f}$	An assignment of the feature modes of the feature variables $\mathbf{C}$.
F	A feature variable, or the fault mode *faulty*.
$\mathbf{F}$	A set of feature variables.
$\mathcal{F}$	A set of assignments of feature variables.
$\mathcal{F}^*$	Family of structures.
G	A graph.

G_π	A solution graph.
h	A heuristic function.
h_l	A lower bound heuristic function.
h_u	An upper bound heuristic function.
I	A troubleshooting problem.
$\mathcal{I}$	Ordering of components when computing the heuristic h_{fixed}.
l	A loss function.
M	A troubleshooting model.
M_P	A probabilistic model.
$\mathcal{N}$	The set of nodes of a graph.
NF	The fault mode *not faulty* of a component variable.
o	An observation mode of the observation variable C.
$\mathbf{o}$	An assignment of the observation modes of the observation variables $\mathbf{C}$.
O	An observation variable.
$\mathbf{O}$	A set of observation variables.
$\mathcal{O}$	A set of POMDP observations.
p	The state transition probability function for MDP:s.
$\mathcal{P}$	The preconditions of an action.
r	A repair event, or the reward function of an MDP.
$\mathbf{r}$	A set of repair events.
s	A state.
$\mathcal{S}$	A set of states.
t	Time.
t_c	The current time.
t_ω	The time of the last operation event.
T	The Bellman update operator.
V_π	The value function of an MDP policy.
w	A weight function.
x	A value of the stochastic variable X.
$\mathbf{x}$	Values of the stochastic variables $\mathbf{X}$.
X	A stochastic variable.
$\mathbf{X}$	A set of stochastic variables.

B

Acronyms

ACC	Automatic Climate Control system
BN	Bayesian Network
BRTDP	Bounded Real-Time Dynamic Programming
CBR	Case-Based Reasoning
CR	Cost of Repair
CPD	Conditional Probability Distribution
CPT	Conditional Probability Table
DAE	Differential Algebraic Equations
DAG	Directed Acyclic Graph
DBN	Dynamic Bayesian Network
DES	Discrete Event System
DTC	Diagnostic Trouble Code
ECR	Expected Cost of Repair
ECU	Electronic Control Unit
FRTDP	Focussed Real-Time Dynamic Programming
GDE	General Diagnostic Engine
HSVI	Heuristic Search Value Iteration
IBLAO*	Iterative Bounding LAO*
ILAO*	Improved LAO*
LAO*	Algorithm for solving cyclic AND/OR graphs
MDP	Markov Decision Process
nsDBN	Non-stationary Dynamic Bayesian Network

NF	Not Faulty
OBD	On-Board Diagnosis
PBVI	Point-Based Value Iteration
POMDP	Partially Observable Markov Decision Process
RTDP	Real-Time Dynamic Programming
SSPP	Stochastic Shortest Path Problem
VPI-RTDP	Value of Perfect Information Real-Time Dynamic Programming
wIBLAO*	Iterative Bounding LAO* using a weight function

C

The Retarder Model File

The format for the retarder model file is in an adapted form of the MSBN format for describing Bayesian networks [25].

```
trouble network "Scania Retarder Auxiliary Braking System"
//Components
node FC {
  name: "System status";
  category: "nonpersistent";
  type: discrete[2] = {"Not faulty", "Faulty"};
}
node C01 {
  name: "Filter, oil cooler";
  category: "persistent";
  type: discrete[2] = {"Not faulty", "clogged"};
}
node C02 {
  name: "Temp. sensor, coolant";
  category: "persistent";
  type: discrete[2] = {"Not faulty", "Faulty"};
}
node C03 {
  name: "Temp. sensor, oil";
  category: "persistent";
  type: discrete[2] = {"Not faulty", "Faulty"};
}
node C04 {
  name: "Gasket, gearbox side";
  category: "persistent";
  type: discrete[2] = {"Not faulty", "Leaking"};
}
node C05 {
  name: "Magnet valves";
  category: "persistent";
  type: discrete[3] = {"Not faulty", "Stuck", "Leakage"};
}
node C06 {
  name: "Proportional valve";
  category: "persistent";
  type: discrete[3] = {"Not faulty", "Stuck", "Leakage"};
}
node C07 {
  name: "Pres. sensor, oil";
  category: "persistent";
  type: discrete[2] = {"Not faulty", "Faulty"};
}
node C08 {
  name: "Air tube";
  category: "persistent";
  type: discrete[2] = {"Not faulty", "Leakage"};
}
node C09 {
  name: "Air valves";
  category: "persistent";
  type: discrete[2] = {"Not faulty", "Leakage"};
}
node C10 {
  name: "Control valve";
  category: "persistent";
  type: discrete[2] = {"Not faulty", "Faulty"};
}
node C11 {
  name: "Accumulator";
  category: "persistent";
  type: discrete[2] = {"Not faulty", "Faulty"};
}
node C12 {
  name: "Bearing";
  category: "persistent";
  type: discrete[2] = {"Not faulty", "Faulty"};
}
node C13 {
  name: "Pump";
  category: "persistent";
  type: discrete[2] = {"Not faulty", "Faulty"};
}
node C14 {
  name: "Iron goods";
  category: "persistent";
  type: discrete[2] = {"Not faulty", "Faulty"};
}
node C15 {
  name: "Oil";
  category: "persistent";
  type: discrete[2] = {"Not faulty", "Poor quality"};
}
node C16 {
  name: "Radial gasket, retarder";
  category: "persistent";
  type: discrete[2] = {"Not faulty", "Leakage"};
}
node C17 {
  name: "Gasket, retarder side";
  category: "persistent";
  type: discrete[2] = {"Not faulty", "Leakage"};
}
node C18 {
  name: "Radial gasket, gearbox";
  category: "persistent";
  type: discrete[2] = {"Not faulty", "Leakage"};
}
node C19 {
  name: "Cables ECU";
  category: "persistent";
  type: discrete[3] = {"Not faulty", "Break, ret side", "Break, ECU side"};
}
node C20 {
  name: "ECU";
  category: "persistent";
  type: discrete[2] = {"Not faulty", "Faulty"};
}
//Observations
node O01 {
  name: "Oil temp.";
  category: "nonpersistent";
  type: discrete[2] = {"Normal", "High"};
}
node O02 {
  name: "Retarder disengagement";
  category: "nonpersistent";
  type: discrete[2] = {"Normal", "Early"};
}
node O03 {
  name: "Engine warning lamp";
  category: "nonpersistent";
  type: discrete[2] = {"Not lit", "Lit"};
}
node O04 {
  name: "Cooler";
  category: "nonpersistent";
  type: discrete[2] = {"Normal", "Oil stained"};
}
node O05 {
  name: "Torque";
  category: "nonpersistent";
  type: discrete[2] = {"Normal", "Uncontrollable"};
}
node O06 {
  name: "Torque, driver";
  category: "nonpersistent";
  type: discrete[2] = {"Normal", "Uncontrollable"};
}
node O07 {
  name: "Torque, mech.";
  category: "nonpersistent";
  type: discrete[2] = {"Normal", "Uncontrollable"};
}
node O08 {
  name: "DTC: unplausible coolant temp.";
  category: "nonpersistent";
  type: discrete[2] = {"Not indicating", "Indicating"};
}
node O09 {
  name: "DTC: unplausible oil temp.";
  category: "nonpersistent";
  type: discrete[2] = {"Not indicating", "Indicating"};
}
node O10 {
  name: "Vis. leakage, magnet valves";
  category: "nonpersistent";
  type: discrete[2] = {"Not indicating", "Indicating"};
}
node O11 {
  name: "Vis. leakage, prop. valve";
  category: "nonpersistent";
  type: discrete[2] = {"Not indicating", "Indicating"};
}
node O12 {
  name: "DTC: unplausible oil pres.";
  category: "nonpersistent";
  type: discrete[2] = {"Not indicating", "Indicating"};
}
node O13 {
  name: "Vis. leakage, control valve";
  category: "nonpersistent";
  type: discrete[2] = {"Not indicating", "Indicating"};
}
node O14 {
  name: "Leakage, air tube";
  category: "nonpersistent";
  type: discrete[2] = {"Not indicating", "Indicating"};
}
node O15 {
  name: "Leakage, air valves";
  category: "nonpersistent";
  type: discrete[2] = {"Not indicating", "Indicating"};
}
node O16 {
  name: "Retarder engagement";
  category: "nonpersistent";
  type: discrete[2] = {"Normal", "Late"};
}
node O17 {
  name: "Braking force";
  category: "nonpersistent";
  type: discrete[2] = {"Normal", "Bad"};
}
node O18 {
  name: "Oil quality";
  category: "nonpersistent";
  type: discrete[2] = {"Normal", "Bad"};
}
node O19 {
  name: "Oil level, gearbox";
  category: "nonpersistent";
  type: discrete[2] = {"Normal", "Low"};
}
node O20 {
  name: "Oil level, retarder";
  category: "nonpersistent";
  type: discrete[2] = {"Normal", "Low"};
}
node O22 {
  name: "Noise shield";
  category: "nonpersistent";
  type: discrete[2] = {"Normal", "Oil stained"};
}
node O23 {
  name: "ECU cables, ret. side";
  category: "nonpersistent";
  type: discrete[2] = {"Normal", "Visible damage"};
}
node O24 {
  name: "ECU cables, ECU side";
  category: "nonpersistent";
  type: discrete[2] = {"Normal", "Visible damage"};
}
node O25 {
  name: "DTC: ECU connectors";
  category: "nonpersistent";
  type: discrete[2] = {"Not indicating", "Indicating"};
}
node O26 {
  name: "DTC: ECU internal";
  category: "nonpersistent";
  type: discrete[2] = {"Not indicating", "Indicating"};
}
//Feature variables
node F01 {
  name: "Vehicle";
  category: "feature";
  type: discrete[2] = {"In workshop", "Outside workshop"};
}
node F02 {
  name: "Cab";
  category: "feature";
  type: discrete[2] = {"Closed", "Tilted"};
}
node F03 {
  name: "Frame support";
  category: "feature";
  type: discrete[2] = {"Removed", "Fit"};
}
node F04 {
  name: "Noise shield";
  category: "feature";
  type: discrete[2] = {"Fit", "Removed"};
}
node F05 {
  name: "Retarder oil";
  category: "feature";
  type: discrete[2] = {"Filled", "Drained"};
}
node F06 {
  name: "Gearbox oil";
  category: "feature";
  type: discrete[2] = {"Filled", "Drained"};
}
node F07 {
  name: "Coolant";
  category: "feature";
  type: discrete[2] = {"Filled", "Drained"};
}
node F08 {
  name: "Proportional valve";
  category: "feature";
  type: discrete[2] = {"Fit", "Removed"};
}
node F09 {
  name: "Propeller shaft";
  category: "feature";
  type: discrete[2] = {"Fit", "Removed"};
}
node F10 {
  name: "Oil cooler";
  category: "feature";
  type: discrete[2] = {"Fit", "Removed"};
}
node F11 {
  name: "Retarder unit";
  category: "feature";
  type: discrete[2] = {"Fit", "Removed"};
}
node F12 {
  name: "Retarder housing";
  category: "feature";
  type: discrete[2] = {"Assembled", "Disassembled"};
}
node F13 {
  name: "Retarder axle";
  category: "feature";
  type: discrete[2] = {"Fit", "Removed"};
}
//Conditional probabilities
probability(C01) {
  0.9965, 0.0035;
}
probability(C02) {
  0.9925, 0.0075;
}
probability(C03) {
  0.998, 0.002;
}
probability(C04) {
  0.997, 0.003;
}
probability(C05) {
  0.997, 0.002, 0.001;
}
probability(C06) {
  0.994, 0.005, 0.001;
}
probability(C07) {
  0.9965, 0.0035;
}
probability(C08) {
  0.9965, 0.0035;
}
probability(C09) {
  0.998, 0.002;
}
probability(C10) {
  0.9945, 0.0055;
}
```

```
probability(C11) {
  0.9945, 0.0055;
}
probability(C12) {
  0.998, 0.002;
}
probability(C13 | C12) {
  (0): 0.999, 0.001;
  (1): 0, 1;
}
probability(C14) {
  0.999, 0.001;
}
probability(C15) {
  0.9995, 0.0005;
}
probability(C16 | C15) {
  (0): 0.999, 0.001;
  (1): 0.2, 0.8;
}
probability(C17) {
  0.999, 0.001;
}
probability(C18) {
  0.997, 0.003;
}
probability(C19) {
  0.9955, 0.003, 0.0015;
}
probability(C20) {
  0.999, 0.001;
}
probability(O01 | C01, C02, C03, C10) {
  function: nor;
  (0, 0, 0, 0): 1, 0;
  (1, 0, 0, 0): 0, 1;
  (0, 1, 0, 0): 0.1, 0.9;
  (0, 0, 1, 0): 0, 1;
  (0, 0, 0, 1): 0, 1;
}
probability(O02 | C04) {
  (0): 1, 0;
  (1): 0.01, 0.99;
}
probability(O03 | O19, O20) {
  function: nor;
  (0, 0): 1, 0;
  (1, 0): 0, 1;
  (0, 1): 0, 1;
}
probability(O04 | C04) {
  type: "NI";
  (0): 1, 0;
  (1): 0.01, 0.99;
}
probability(O05 | C05, C06, C10) {
  function: nor;
  (0, 0, 0): 1, 0;
  (1, 0, 0): 0.001, 0.999;
  (2, 0, 0): 0.2, 0.8;
  (0, 1, 0): 0.001, 0.999;
  (0, 2, 0): 0.2, 0.8;
  (0, 0, 1): 0.001, 0.999;
}
probability(O06 | O05) {
  (0): 0.99, 0.01;
  (1): 0.01, 0.99;
}
probability(O07 | O05) {
  (0): 1, 0;
  (1): 0, 1;
}
probability(O08 | C02, C05, C06, C08, C09) {
  type: "I", "NI", "NI", "NI", "NI";
  function: nor;
  (0, 0, 0, 0, 0): 1, 0;
  (1, 0, 0, 0, 0): 0, 1;
  (0, 1, 0, 0, 0): 0.05, 0.95;
  (0, 2, 0, 0, 0): 0.95, 0.05;
  (0, 0, 1, 0, 0): 0.05, 0.95;
  (0, 0, 2, 0, 0): 0.95, 0.05;
  (0, 0, 0, 1, 0): 0.2, 0.8;
  (0, 0, 0, 0, 1): 0.2, 0.8;
}
probability(O09 | C01, C03, C05, C06, C08, C09) {
  type: "NI", "I", "NI", "NI", "NI", "NI";
  function: nor;
  (0, 0, 0, 0, 0, 0): 1, 0;
  (1, 0, 0, 0, 0, 0): 0.01, 0.99;
  (0, 1, 0, 0, 0, 0): 0, 1;
  (0, 0, 1, 0, 0, 0): 0.05, 0.95;
  (0, 0, 2, 0, 0, 0): 0.95, 0.05;
  (0, 0, 0, 1, 0, 0): 0.05, 0.95;
  (0, 0, 0, 2, 0, 0): 0.95, 0.05;
  (0, 0, 0, 0, 1, 0): 0.2, 0.8;
  (0, 0, 0, 0, 0, 1): 0.2, 0.8;
}
probability(O10 | C05, C06) {
  type: "NI", "NI";
  function: nor;
  (0, 0): 1, 0;
  (1, 0): 1, 0;
  (2, 0): 0, 1;
  (0, 1): 1, 0;
  (0, 2): 0.9, 0.1;
}
probability(O11 | C05, C06) {
  type: "NI", "NI";
  function: nor;
  (0, 0): 1, 0;
  (1, 0): 1, 0;
  (2, 0): 0.9, 0.1;
  (0, 1): 1, 0;
  (0, 2): 0, 1;
}
probability(O12 | C05, C06, C07, C08, C09) {
  type: "NI", "NI", "I", "NI", "NI";
  function: nor;
  (0, 0, 0, 0, 0): 1, 0;
  (1, 0, 0, 0, 0): 0.05, 0.95;
  (2, 0, 0, 0, 0): 0.95, 0.05;
  (0, 1, 0, 0, 0): 0.05, 0.95;
  (0, 2, 0, 0, 0): 0.95, 0.05;
  (0, 0, 1, 0, 0): 0, 1;
  (0, 0, 0, 1, 0): 0.2, 0.8;
  (0, 0, 0, 0, 1): 0.2, 0.8;
}
probability(O13 | C06, C10) {
  type: "NI", "NI";
  function: nor;
  (0, 0): 1, 0;
  (1, 0): 1, 0;
  (2, 0): 0.9, 0.1;
  (0, 1): 0, 1;
}
probability(O14 | C08, C09) {
  function: nor;
  (0, 0): 1, 0;
  (1, 0): 0, 1;
  (0, 1): 0.9, 0.1;
}
probability(O15 | C08, C09) {
  function: nor;
  (0, 0): 1, 0;
  (1, 0): 0.9, 0.1;
  (0, 1): 0, 1;
}
probability(O16 | C11, C13, C20) {
  function: nor;
  (0, 0, 0): 0.99, 0.01;
  (1, 0, 0): 0.01, 0.99;
  (0, 1, 0): 0.01, 0.99;
  (0, 0, 1): 0.1, 0.9;
}
probability(O17 | C10, C11, C13) {
  function: nor;
  (0, 0, 0): 1, 0;
  (1, 0, 0): 0.05, 0.05;
  (0, 1, 0): 0.01, 0.99;
  (0, 0, 1): 0, 1;
}
probability(O18 | C15) {
  (0): 1, 0;
  (1): 0, 1;
}
probability(O19 | C04, C06, C16, C17) {
  type: "NI", "NI", "NI", "NI";
  function: nor;
  (0, 0, 0, 0): 1, 0;
  (1, 0, 0, 0): 0, 0;
  (0, 1, 0, 0): 1, 0;
  (0, 2, 0, 0): 0.1, 0.9;
  (0, 0, 1, 0): 0.1, 0.9;
  (0, 0, 0, 1): 0.2, 0.8;
}
probability(O20 | C14, C17, C18) {
  type: "NI", "NI", "NI";
  function: nor;
  (0, 0, 0): 1, 0;
  (1, 0, 0): 0, 1;
  (0, 1, 0): 0.2, 0.8;
  (0, 0, 1): 0, 1;
}
probability(O22 | C14, C16) {
  type: "NI", "NI";
  function: nor;
  (0, 0): 1, 0;
  (1, 0): 0, 1;
  (0, 1): 0.01, 0.99;
}
probability(O23 | C19) {
  (0): 1, 0;
  (1): 0, 1;
  (2): 1, 0;
}
probability(O24 | C19) {
  (0): 1, 0;
  (1): 1, 0;
  (2): 0, 1;
}
probability(O25 | C19, C20) {
  function: nor;
  (0, 0): 1, 0;
  (1, 0): 0, 1;
  (2, 0): 0, 1;
  (0, 1): 0.1, 0.9;
}
probability(O26 | C20) {
  (0): 1, 0;
  (1): 0.1, 0.9;
}
probability(FC | C01, C02, C03, C04, C05, C06, C07, C08, C09, C10,
 C11, C12, C13, C14, C15, C16, C17, C18, C19, C20) {
  function: nor;
  (0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0): 1, 0;
  (1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0): 0, 1;
  (0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0): 0, 1;
  (0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0): 0, 1;
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  (0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0): 0, 1;
  (0, 0, 0, 0, 2, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0): 0, 1;
  (0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0): 0, 1;
  (0, 0, 0, 0, 0, 2, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0): 0, 1;
  (0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0): 0, 1;
  (0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0): 0, 1;
  (0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0): 0, 1;
  (0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0): 0, 1;
  (0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0): 0, 1;
  (0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0): 0, 1;
  (0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0): 0, 1;
  (0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0): 0, 1;
  (0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0): 0, 1;
  (0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0): 0, 1;
  (0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0): 0, 1;
  (0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0): 0, 1;
  (0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0): 0, 1;
  (0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 2, 0): 0, 1;
  (0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1): 0, 1;
}
//Actions
```

```
action AFC {
  name: Test drive;
  preconditions: F01 = 0;
  effects:  operate 900, observe FC;
  cost = 125;
}
action ARC01 {
  name: Replace oil filter;
  preconditions: F05 = 1;
  effects: do C01 = 0;
  cost = 45;
}
action ARC02 {
  name: Replace temp. sensor, coolant;
  preconditions: F06 = 1;
  effects: do C02 = 0;
  cost = 145;
}
action ARC03 {
  name: Replace temp. sensor, oil;
  preconditions: F06 = 1;
  effects: do C03 = 0;
  cost = 150;
}
action ARC04 {
  name: Replace gasket, gearbox side;
  preconditions: F11 = 1;
  effects: do C04 = 0;
  cost = 90;
}
action ARC05 {
  name: Replace magnet valves;
  preconditions: F12 = 1;
  effects: do C05 = 0;
  cost = 310;
}
action ARC06 {
  name: Replace proportional valve;
  preconditions: F12 = 1;
  effects: do C06 = 0;
  cost = 240;
}
action ARC07 {
  name: Replace pres. sensor, oil;
  preconditions: F06 = 1;
  effects: do C07 = 0;
  cost = 190;
}
action ARC08 {
  name: Replace air tube;
  preconditions: F03 = 1, F04 = 1;
  effects: do C08 = 0;
  cost = 150;
}
action ARC09 {
  name: Replace air valves;
  preconditions: F03 = 1, F04 = 1;
  effects: do C09 = 0;
  cost = 150;
}
```

```
action ARC10 {
  name: Replace control valve;
  preconditions: F12 = 1;
  effects: do C10 = 0;
  cost = 390;
}
action ARC11 {
  name: Replace accumulator;
  preconditions: F12 = 1;
  effects: do C11 = 0;
  cost = 790;
}
action ARC12 {
  name: Replace bearing;
  preconditions: F10 = 1;
  effects: do C12 = 0;
  cost = 130;
}
action ARC13 {
  name: Replace pump;
  preconditions: F12 = 1;
  effects: do C13 = 0;
  cost = 120;
}
action ARC14 {
  name: Replace iron goods;
  preconditions: F12 = 1;
  effects: do C14 = 0;
  cost = 2000;
}
action ARC16 {
  name: Replace radial gasket, retarder;
  preconditions: F13 = 1;
  effects: do C16 = 0;
  cost = 260;
}
action ARC17 {
  name: Replace gasket, retarder side;
  preconditions: F11 = 1;
  effects: do C17 = 0;
  cost = 120;
}
action ARC18 {
  name: Replace radial gasket, gearbox;
  preconditions: F13 = 1;
  effects: do C18 = 0;
  cost = 265;
}
action ARC19 {
  name: Replace cables, ECU;
  preconditions: F11 = 1;
  effects: do C19 = 0;
  cost = 200;
}
action ARC20 {
  name: Replace ECU;
  preconditions: F02 = 1;
  effects: do C20 = 0;
  cost = 2200;
}
```

```
action AOC02 {
  name: Inspect temp. sensor coolant;
  preconditions: F06 = 1;
  effects: observe C02;
  cost = 40;
}
action AOC03 {
  name: Inspect temp. sensor oil;
  preconditions: F06 = 1;
  effects: observe C03;
  cost = 25;
}
action AOC04 {
  name: Inspect gasket, gearbox side;
  preconditions: F11 = 1;
  effects: observe C04;
  cost = 45;
}
action AOC07 {
  name: Inspect pres sensor oil;
  preconditions: F06 = 1;
  effects: observe C07;
  cost = 22;
}
action AOC12 {
  name: Inspect bearing;
  preconditions: F12 = 1;
  effects: observe C12;
  cost = 34;
}
action AOC13 {
  name: Inspect pump;
  preconditions: F12 = 1;
  effects: observe C13;
  cost = 25;
}
action AOC14 {
  name: Inspect iron goods;
  preconditions: F12 = 1;
  effects: observe C14;
  cost = 75;
}
action AOC16 {
  name: Inspect radial gasket, retarder;
  preconditions: F13 = 1;
  effects: observe C16;
  cost = 16;
}
action AOC17 {
  name: Inspect gasket, retarder side;
  preconditions: F11 = 1;
  effects: observe C17;
  cost = 25;
}
action AOC18 {
  name: Inspect radial gasket, gearbox;
  preconditions: F13 = 1;
  effects: observe C18;
  cost = 75;
}
```

```
action A0004 {
  name: Check for oil on cooler;
  preconditions: F03 = 1, F04 = 1;
  effects: observe O04;
  cost = 16;
}
action A0010 {
  name: Check for leakage, magn. valves;
  preconditions: F08 = 1;
  effects: observe O10;
  cost = 50;
}
action A0011 {
  name: Check for leakage, prop. valve;
  preconditions: F03 = 1, F04 = 1;
  effects: observe O11;
  cost = 70;
}
action A0013 {
  name: Check for leakage, control valve;
  preconditions: F03 = 1, F04 = 1;
  effects: observe O13;
  cost = 80;
}
action A0014 {
  name: Check for air leakage;
  preconditions: F03 = 1, F04 = 1;
  effects: observe O14, observe O15;
  cost = 50;
}
action A0018 {
  name: Check oil quality;
  preconditions: F05 = 1;
  effects: observe O18;
  cost = 20;
}
action A0019 {
  name: Check oil level, retarder;
  preconditions: F02 = 1;
  effects: observe O19;
  cost = 10;
}
action A0020 {
  name: Check oil level, gearbox;
  preconditions: F02 = 1;
  effects: observe O20;
  cost = 10;
}
action A0023 {
  name: Check ECU cables, ret. side;
  preconditions: F03 = 1, F04 = 1;
  effects: observe O23;
  cost = 34;
}
action A0024 {
  name: Check ECU cables, ECU side;
  preconditions: F02 = 1;
  effects: observe O24;
  cost = 34;
}
```

```
action A0007 {
  name: Check retarder performance;
  preconditions: F01 = 1;
  effects: observe 007, observe 016, observe 017, operate 90;
  cost = 100;
}
action ADF01 {
  name: Drive in vehicle;
  preconditions: F01 = 0;
  effects: do F01 = 1, operate 30;
  cost = 15;
}
action AAF01 {
  name: Drive out vehicle;
  preconditions: F01 = 1, F02 = 0, F03 = 0, F04 = 0, F05 = 0;
  effects: do F01 = 0, operate 30;
  cost = 15;
}
action ADF02 {
  name: Tilt cab;
  preconditions: F02 = 0, F01 = 1;
  effects: do F02 = 1;
  cost = 28;
}
action AAF02 {
  name: Close cab;
  preconditions: F02 = 1;
  effects: do F02 = 0;
  cost = 30;
}
action ADF03 {
  name: Fit frame support;
  preconditions: F03 = 0, F01 = 1;
  effects: do F03 = 1;
  cost = 24;
}
action AAF03 {
  name: Remove frame support;
  preconditions: F03 = 1, F06 = 0, F07 = 0, F08 = 0;
  effects: do F03 = 0;
  cost = 3;
}
action ADF04 {
  name: Remove noise shield;
  preconditions: F04 = 0, F01 = 1;
  effects: do F04 = 1, observe 022;
  cost = 10;
}
action AAF04 {
  name: Fit noise shield;
  preconditions: F04 = 1, F07 = 0;
  effects: do F04 = 0;
  cost = 5;
}
action ADF05 {
  name: Drain retarder oil;
  preconditions: F05 = 0, F01 = 1;
  effects: do F05 = 1;
  cost = 5;
}
```

```
action AAF05 {
  name: Fill retarder oil;
  preconditions: F05 = 1, F08 = 0, F09 = 0, F10 = 0;
  effects: do F05 = 0, do C15 = 0;
  pfail = (C15 | 1, 0);
  cost = 64;
}
action ADF06 {
  name: Drain coolant;
  preconditions: F06 = 0, F03 = 1;
  effects: do F06 = 1;
  cost = 5;
}
action AAF06 {
  name: Fill coolant;
  preconditions: F06 = 1, F09 = 0;
  effects: do F06 = 0;
  cost = 66;
}
action ADF07 {
  name: Drain gearbox oil;
  preconditions: F07 = 0, F03 = 1, F04 = 1;
  effects: do F07 = 1;
  cost = 18;
}
action AAF07 {
  name: Fill gearbox oil;
  preconditions: F07 = 1, F09 = 0, F10 = 0;
  effects: do F07 = 0;
  cost = 68;
}
action ADF08 {
  name: Remove proportional valve;
  preconditions: F08 = 0, F03 = 1, F05 = 1;
  effects: do F08 = 1;
  cost = 47;
}
action AAF08 {
  name: Fit proportional valve;
  preconditions: F08 = 1, F11 = 0;
  effects: do F08 = 0;
  cost = 45;
}
action ADF09 {
  name: Remove propeller shaft;
  preconditions: F09 = 0, F05 = 1, F06 = 1, F07 = 1;
  effects: do F09 = 1;
  cost = 20;
}
action AAF09 {
  name: Fit propeller shaft;
  preconditions: F09 = 1, F11 = 0;
  effects: do F09 = 0;
  cost = 33;
}
action ADF10 {
  name: Remove oil cooler;
  preconditions: F10 = 0, F05 = 1, F07 = 1;
  effects: do F10 = 1;
  cost = 94;
}
action AAF10 {
  name: Fit propeller shaft;
  preconditions: F10 = 1, F11 = 0;
  effects: do F10 = 0;
  cost = 86;
}
action ADF11 {
  name: Remove retarder;
  preconditions: F11 = 0, F09 = 1, F10 = 1;
  effects: do F11 = 1;
  cost = 76;
}
action AAF11 {
  name: Fit retarder;
  preconditions: F11 = 1, F12 = 0;
  effects: do F11 = 0;
  cost = 54;
}
action ADF12 {
  name: Disassemble ret. housing;
  preconditions: F12 = 0, F11 = 1;
  effects: do F12 = 1;
  cost = 160;
}
action AAF12 {
  name: Assemble ret. housing;
  preconditions: F12 = 1, F13 = 0;
  effects: do F12 = 0;
  cost = 332;
}
action ADF13 {
  name: Remove retarder axle;
  preconditions: F13 = 0, F12 = 1;
  effects: do F13 = 1;
  cost = 55;
}
action AAF13 {
  name: Fit retarder axle;
  preconditions: F13 = 1;
  effects: do F13 = 0;
  cost = 23;
}
```

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Titel
Title

Computer-Assisted Troubleshooting for Efficient Off-board Diagnosis

Författare
Author

Håkan Warnquist

Sammanfattning
Abstract

This licentiate thesis considers computer-assisted troubleshooting of complex products such as heavy trucks. The troubleshooting task is to find and repair all faulty components in a malfunctioning system. This is done by performing actions to gather more information regarding which faults there can be or to repair components that are suspected to be faulty. The expected cost of the performed actions should be as low as possible.

The work described in this thesis contributes to solving the troubleshooting task in such a way that a good trade-off between computation time and solution quality can be made. A framework for troubleshooting is developed where the system is diagnosed using non-stationary dynamic Bayesian networks and the decisions of which actions to perform are made using a new planning algorithm for Stochastic Shortest Path Problems called Iterative Bounding LAO*.

It is shown how the troubleshooting problem can be converted into a Stochastic Shortest Path problem so that it can be efficiently solved using general algorithms such as Iterative Bounding LAO*. New and improved search heuristics for solving the troubleshooting problem by searching are also presented in this thesis.

The methods presented in this thesis are evaluated in a case study of an auxiliary hydraulic braking system of a modern truck. The evaluation shows that the new algorithm Iterative Bounding LAO* creates troubleshooting plans with a lower expected cost faster than existing state-of-the-art algorithms in the literature. The case study shows that the troubleshooting framework can be applied to systems from the heavy vehicles domain.

Nyckelord
Keywords

Automated planning, diagnosis, automotive industry, troubleshooting, Bayesian networks,

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