PREDICTING AND DIAGNOSING FAULTS IN WASTEWATER TREATMENT PROCESS BY BAYESIAN BELIEF NETWORKS

HOCK GUAN CHONG

Doctor of Philosophy

THE UNIVERSITY OF ASTON IN BIRMINGHAM

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Hock Guan Chong
Doctor of Philosophy
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THESIS SUMMARY

Diagnosing faults in wastewater treatment, like diagnosis of most problems, requires bi-directional plausible reasoning. This means that both predictive (from causes to symptoms) and diagnostic (from symptoms to causes) inferences have to be made, depending on the evidence available, in reasoning for the final diagnosis. The use of computer technology for the purpose of diagnosing faults in wastewater process has been explored, and a rule-based expert systems was initiated. It was found that such approach has serious limitations in its ability to reason bi-directionally, which makes it unsuitable for diagnosing tasks under the conditions of uncertainty. The probabilistic approach known as Bayesian Belief Networks(BBNs) was then critically reviewed, and was found to be well-suited for diagnosis under uncertainty. The theory and application of BBNs are outlined. A full-scale BBN for the diagnosis of faults in a wastewater treatment plant based on the activated sludge system has been developed in this research. Results from the BBN show good agreement with the predictions of wastewater expert. It can be concluded that the BBNs are far superior to rule-based systems based on certainty factors in their ability to diagnose faults and predict symptoms in complex operating systems having inherently uncertain behaviour.

Key words: expert systems, reasoning under uncertainty, rule-based systems, Bayesian Belief Networks, wastewater treatment.

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CHAPTER 1 INTRODUCTION

The treatment of wastewater involves complex processes that are dynamic in nature. Changes in the flow rate, concentration and composition can often affect the normal operation of the system. Thus such systems require skilled and properly-trained wastewater operators on site to ensure satisfactory system performance, so that treated effluent can consistently comply with regulatory requirements. The challenge that is faced by these operators is to detect early symptoms before any effluent problem occurs. If left unchecked, these problems may escalate into a crisis situation costing heavy penalties and bad publicity for the organization.

Unless the operator is very well-trained and experienced, his/her task may seem quite challenging. Furthermore, the type of skill required is gained mainly from practical field experience rather than through classroom training. The challenge is further compounded by the fact that as new industries are set up, there is usually a shortage of skilled operators. Those who are very skilled may be promoted to a higher position, or simply leave the organization upon retirement. They will take with them their extensive knowledge and experience, with little passed on to their successors or the organization. Though many would like to share their experience, this is usually done on an ad hoc basis, rather than through a systematic approach.

The desire to capture expert knowledge systematically prompted research into the use of computer technology. Although experts' knowledge, especially their heuristic knowledge, may not be fully emulated, research into the use of Artificial Intelligence (AI) has achieved significant success in this field. There are many well-developed techniques in the broad domain of AI, including: expert systems, robotics, neural networks, and visual recognition.

In view of the potential needs, the author initiated a project to conduct research in the wastewater treatment area. The work initially centred around choosing an appropriate AI technique on which to base such work. It was decided that a rule-based expert systems approach be used, because of its good structuring system and the ready availability of commercial tools seemed to best facilitate the system's development. In particular, a software package produced by Creative Logic Limited called LEONARDO was chosen for the work. It was envisaged that an expert system, CLAR_EX (CLARifier EXpert - an expert system for detecting faults in clarifiers), would be developed to fulfill the objectives of this project.

The ensuing work focused on the development of the *knowledge base* for CLAR_EX. The knowledge needed was on the diagnosis of faults found in the clarifiers of an activated sludge wastewater treatment system. So the first step was to conceptualise and put into writing the common symptoms of this process, their causes and recommended remedial actions. A diagram for each symptom was made depicting its linkage to its possible causes. 21 such diagrams, known as Inference Diagrams, were developed and these formed the foundation for transforming this knowledge into computer code that formed the knowledge base of CLAR_EX. The knowledge was originally acquired from literature review and the author's own personal experience, then further verification was made by interviewing domain experts.

A prototype of CLAR_EX was developed. However, in the subsequent work of examining how CLAR_EX could handle uncertainty in the relationship, the author found that it was difficult to implement the necessary interactions between the 21 inference diagrams in a truely representative way.

This can be illustrated by looking at those caused by correlated evidence, which arises when two apparently independent items of evidence relating to a particular cause or causes are later found to have originated from a common source. For example, if you are responsible for the maintenance of a wastewater plant and are informed of excess solids flowing over the weirs of the clarifier from two sources: a message left with your secretary by an operator who is a well-known joker; followed later by a telephone call from a newly appointed plant manager. Your initial doubt about the validity of the first message was overcome when you receive the call from the manager, but was later renewed when you found that the plant manager had gained his information from the same operator. This type of situation creates enormous difficulties in rule-based systems because of their assumption of detachment (that is, how the validity of each rule is independent of its evidence was derived). Chapter 4 fully explores and explains this concept in detail.

In addition, effective diagnosis requires the retraction of belief in a given cause when new evidence implies an alternative cause and explains away the earlier evidence pointing to the first clause. Such retraction requires bi-directional plausible reasoning, that is, predictive (cause to symptom) and diagnostic (symptom to cause). Such capabilities are not available in modular rule-based expert system, for reasons which will be explained later.

The inability of CLAR_EX, and rule-based expert systems in general, to effectively represent problems involving plausible reasoning (that is, problems where the relationships are characterized by the existence of inherent uncertainties) prompted re-consideration of the future direction of this research work. This occurred at a time when Causal Belief Networks were emerging as a powerful new technique in AI. The superiority of this technique over the rule-based system approach with respect to the task at hand was so apparent that it was decided to abandon CLAR_EX and transfer to this new approach.

This was not too great a set back since the inference diagrams developed for CLAR_EX provided a good starting point from which to construct the structure of the causal belief network. The development of this causal network, known as CLAR_NET (CLARifier NETwork - a causal belief network for the detection of faults in clarifiers) basically consisted of two distinct stages - construction of the causal structure, and the estimation of its conditional probabilities. However, subsequent fine tuning of the network involved iterations between the two.

The construction of the causal structure of CLAR_NET involved integrating all the essential components of the 21 inference diagrams into one large network. Subsequent fine tuning was made to decompose some of the nodes having too many *parents* into smaller immediate generations, so that they became *grandparents* or even *great-grandparents*. The reduction in the number of links to each node not only resulted in better computational efficiency of the structure, but also provided a clearer causal relationship between the different entities in the wastewater plant. Subsequently, two domain experts: H.A. Hawkes from Aston University in U.K., and Phil Nungesser from the Bureau of Water Pollution Control in Atlanta, USA were consulted to provide comments on the validity of the network. Their feedback led to further modification of its structure.

In estimating the conditional probabilities, each node was first assigned two or three possible states; for example, low, normal and high. The conditional probabilities associated with these states were initially assigned by the author based on his personal experience of wastewater treatment processes. The structure and conditionally probabilities were then transferred into an Apple Macintosh software package called ERGO to create CLAR_NET. CLAR_NET was then compiled and run to provide the prior beliefs (that is, "no evidence" case) in the states of all the nodes. These showed that several nodes displayed high beliefs in abnormal state, which was clearly erroneous for the 'no evidence' case.

Thus, the next stage was to re-examine all the conditional probabilities and wherever possible, modify them so as to reduce the likelihood of abnormal prior beliefs. By successive adjustments, a modified network with a set of refined conditional probabilities for all the nodes was obtained; in which all the prior beliefs in 'normal' states were at least 90%. The only exception was the 'Influent Type' node which had three states: industrial wastewater only, domestic wastewater only, and mixed domestic/industrial wastewater. Clearly, the concept of normal operation did not apply to this node.

CLAR_NET was then subjected to four types of tests to assess its accuracy of prediction. The first assessment was to determine whether CLAR_NET has the ability to predict results accurately. This was done by putting CLAR_NET under the normal plant condition (denoted as the "No Evidence" case) to check whether all relevant node probabilities obtained were indicative of the "normal" state condition.

The next test was designed to test the behaviour of CLAR_NET under several conditions that could possibly occur in an activated sludge system of a wastewater treatment plant. Forty cases were conducted, of which twenty-three cases were predictive-type cases, and the rest were diagnostic-type. Results were generally found to be acceptable within the range of the author's expectation.

CLAR_NET was then subject to *sensitivity tests* to demonstrate its sensitivity and stability with respect to the evidence received. Eight cases with different sets of evidence were presented. In each case, those nodes within CLAR_NET *d-connected* to the evidence node were examined, and they were colour-coded to illustrate the magnitude of impact due to the evidence received.

The final tests involved presenting to four domain experts with a questionnaire containing case studies. They were asked to predict the likely states of specific nodes in the network, given the states of other selected nodes. The results obtained were compiled and evaluated. For each case, the deviation of CLAR_NET prediction to an expert's response, known as *error* (in terms of percentage), was calculated. From the results obtained from each domain expert, the *average error* using the root mean square (RMS) formula was computed. The CLAR_NET's predictions were found to fall within an acceptable range of those of the experts', with the *RMS of RMSs of error* of only 7.37%. The system was deemed able to predict and diagnose faults in clarifiers serving activated sludge plant to a satisfactory level of precision.

The above summarizes the whole content of this thesis. The following chapter reviews the literature in the two specialist fields which together form the basis of this project; namely: a) biological wastewater treatment systems, b) artificial intelligence and expert systems, and c) the application of expert systems in wastewater engineering. This provides the basis for understanding the motivation for this project, its basic principles and the way in which it developed.

Chapter 3 brings into picture the development of the diagnostic model for clarifiers. The initial work of which was conducted using the rule-based expert system shell, which resulted in the development of the prototype system (CLAR_EX). The stages in its development, its strengths and weaknesses, and especially its inadequacy in handling uncertainty using the certainty factors are highlighted.

The concepts behind the Bayesian Belief Networks are fully explained in Chapter 4, with an Example Network to illustrate its application. Results from cases consulted shows that the network is able to handle plausible reasoning like human experts.

This leads to the development of CLAR_NET, a diagnostic and predictive network for wastewater treatment based on the concept of Bayesian Belief Networks. The process of constructing the causal structure and eliciting the probabilities for CLAR_NET are explained in Chapter 5.

In Chapter 6, the full network of CLAR_NET is subjected to tests to check its accuracy and sensitivity to changes in evidence. The methodologies for these tests and the results are also presented.

Chapter 7 gives a conclusive summary to the above, together with a section on an over-view of the whole project and recommendations for further improvement to the system and possible directions of future research.

Various segments of the work conducted, such as the inference diagrams for CLAR_EX, computer codes for CLAR_EX, transcripts of interviews with domain experts, questionnaire presented to domain experts to check system performance, and references used throughout work here are also contained in the thesis.

CHAPTER 2 LITERATURE REVIEW

2.1 Introduction

Before exploring in detail the application of Bayesian Belief Networks (BBNs) in biological wastewater treatment, it would be more appropriate to fully understand some underlying principles, as well as the research and published work relating to the application of computer technology in the wastewater treatment area.

This chapter will begin with some fundamental concepts of wastewater treatment processes, specifically in relation to the activated sludge system and clarifiers, which are principal components covered in this project. It will then proceed to discuss the concept of Artificial Intelligence (AI) in general, and the application of expert systems in greater detail. Various techniques for handling uncertainty will also be discussed. This will bring forth an understanding of the strengths and limitations of these techniques as a prelude to explaining why the Bayesian technique was finally chosen in preference to the rule-based system.

2.2 Wastewater Treatment Operations in Environmental Protection

2.2.1 Historical Background

Although the earliest sewers known in the Western World were the great underground drains of ancient Rome, wastewater treatment is a comparatively recent development dating from the late 1800s and early 1900s. Development of the germ theory in the latter half of the nineteenth century by Koch and Pasteur marked the beginning of a new era in sanitation [Metcalf and Eddy, 1979].

In England, wastewater treatment and disposal did not receive much attention until the construction of sewerage systems in the mid-1800s after the cholera epidemic which claimed over 25,000 victims between 1848-1854. Because of the small size of British streams, untreated wastewater which discharged into them soon became a nuisancc. As the rivers became adversely polluted and the amount of land suited for wastewater disposal by irrigation was limited, intensive methods of treatment were developed. One of the first recorded wastewater treatment processes used in England was chemical precipitation and sedimentation in 1762. The activated sludge process which is the most common biological wastewater treatment today, can be traced back to England as early as 1882 when the aeration of sewerage in tanks was investigated.

In the United States, wastewater treatment and disposal did not receive as much attention as in England in the late 1800s, because the extent of pollution caused by wastewater discharged into the relatively large bodies of water was not as marked, and also there were greater areas for land treatment of wastewater. The first septic tanks used in the United States were reported in 1876, and in 1887 the Lawrence Experiment Station was established by the Massachusetts State Board of Health to study both water and wastewater treatment [Department of Army, 1975]. The research at Lawrence produced many intensive wastewater treatment methods. By 1948, wastewater treatment plants served some 45 million Americans out of a total population of 145 million people. A needs survey indicated that in 1980 there were approximately 15,251 wastewater treatment facilities in the United States serving a total population of 157 million people, and it was projected that in the year 2000 there will be 21,600 treatment facilities serving 247 million people [U.S.EPA, 1981].

2.2.2 Biological Wastewater Treatment Using Activated Sludge System

Recent studies show that environmental standards imposed by regulatory agencies are defining the technologies needed for effective operation of wastewater treatment systems [Wett, 1995]. However, the conventional method of biological wastewater treatment using the activated sludge process still proves to be both cost effective and efficient.

The activated sludge process involves treating sewage and other bio-degradable waste water, by aerating and agitating the liquid in admixture with activated sludge, and subsequently separating it from the treated effluent by settlement. Activated sludge can be defined as the flocculant microbial mass which is produced when sewage is continuously aerated. It consists mainly of organisms which are able to metabolize and break down the principal contaminants of waste water.

Some of the sludge is returned for re-use with the excess being discharged as waste sludge. The returned sludge is called return activated sludge (RAS). It has been estimated that about 50% of the sewage in the United Kingdom is treated in activated-sludge plant [The Institute of Water Pollution Control, 1987].

Figure 2.1 Shows a typical layout plan of the biological wastewater treatment plant using an activated sludge process. It should be noted that the configuration of the treatment components within the layout plan can vary depend on the nature and volume of the influent waste water to be treated, and the desired quality of the effluent.

When waste water enters a treatment plant, it usually flows through a series of pretreatment processes such as screening, shredding and grit removal. Coarse materials in the waste water are removed. In addition, an oil-water separator is used to remove the oil if it is contained in the influent.

The wastewater then receives primary treatment. This process is usually done in the primary clarifier where some of the solids carried by the waste water will settle down or float to the water surface. The solids are separated from the wastewater being treated.

Secondary treatment processes follow primary treatment. For the activated sludge process, this usually consists of an aeration basin and a secondary clarifier. Microorganisms digest dissolved organic wastes in an aeration basin, generating biological solids that are removed in the secondary clarifier.

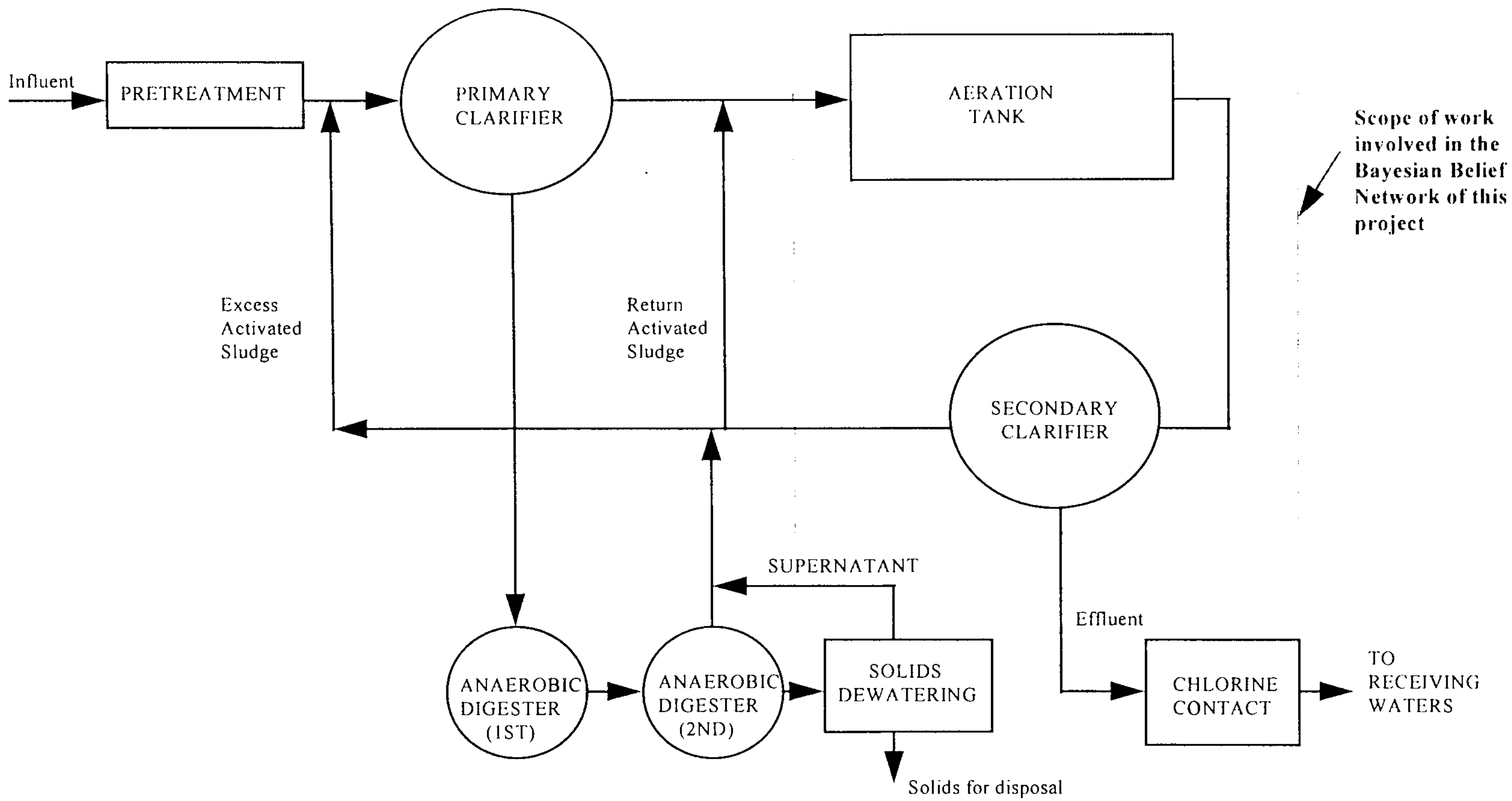

Figure 2.1 Typical layout of a wastewater treatment system using the activated sludge process

The waste sludge removed from the clarifier then goes to the solids handling facilities such as anaerobic digesters and dewatering equipment to thicken and compact the sludge for easy disposal. The clean effluent from the secondary clarifier is usually disinfected by chlorination or by using ultra-violet light to remove pathogenic organisms before being discharged to the receiving stream.

The whole range of processes used in biological treatment systems and the mechanisms involved in each of these processes are described in detail in most of the standard texts on wastewater treatment, such as the MOP/11: Operations of Wastewater Treatment Design (WPCF [1985]).

As the scope of this project deals with the diagnosis of faults in activated sludge system, the following will explain in greater detail the functions of the activated sludge process. In particular, the process involved in the aeration basin and the secondary clarifier.

2.2.3 Aeration Basin Operations

The aeration basin can be in the form of a deep tank of square cross-section, or a ditch in the form of an oval circuit, or a large extensive rectangular tank.

The influent wastewater containing the biodegradable wastes is inoculated with recycled activated sludge as it enters the aeration basin. The mixture, referred to as the "mixed liquor", is then subjected to a period of aeration when it flows through the basin. This "retention" period differs from one treatment plant to another. As a guide, in British practice, it is usual to provide a nominal retention period of at least 5 hours based on the daily dry weather flow to produce a non-nitrified 30 mg/l suspended solids and 20 mg/l BOD effluent from domestic sewage [Curds and Hawkes, 1983]. Figure 2.2 shows the main process involved in removal of organic matter from influent wastewater in the aeration basin and clarifier using the activated sludge process.

Aeration is usually provided by mechanical aerators, and the process serves two important functions:

- to supply adequate oxygen for the respiratory activity of the microorganisms which are mostly aerobes; and
- to maintain the flocs in a continuous state of agitated suspension to ensure maximum contact between them and the waste.

When the activated sludge is mixed with the influent wastewater, there is a rapid uptake of some components of the waste by the sludge flocs which results in rapid reduction of Biochemical Oxygen Demand (BOD) of the wastewater. The rapid removal of waste is achieved by a combination of processes such as adsorption, flocculation of soluble and colloidal matter on the floc surfaces, and the entrainment of particulate solids in the floc matrix.

The growth of the microbial population and the accumulation of non-biodegradable solids result in an increase in the amount of activated sludge. If aeration is continued in the absence of external substrate, then the microorganisms will utilize their own cellular contents, and this subsequently reduces the activated sludge.

From the aeration basin, the mixed liquor flows to clarifier where, under relatively quiescent conditions, the sludge separates from the purified liquor by settlement.

2.2.4 Clarifier Operations

Clarifiers, also known as sedimentation basins, are one of the most common units in wastewater treatment operations and one of the most economical unit processes for pollutant removal [MOP/11, 1976]. They provide early detection of unusual characteristics of influent wastewater and therefore provide protection to downstream treatment units. No other single wastewater treatment unit provides as much opportunity

Figure 2.2 Activated sludge process - showing the biosynthesis and biodegration of organic matter (after Curds and Hawkes, 1983)

Aston University

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Figure 2.3 Cross-section of a typical circular clarifier (after California State University and U.S. E.P.A., 1988) for detection of conditions that affect the rest of the plant. A typical clarifier is shown in Figure 2.3.

Settleable solids in clarifiers comprise of granular and flocculent materials that settle under quiescent condition in a reasonable time (say 1 hour). Non-settleable solids are divided so finely that they will not settle, and chemical treatment is used to remove these fine solids. Factors influencing the rate of sedimentation in clarifiers are tank configuration and influent wastewater characteristics. The removal rate of granular particles depends on tank surface area, whereas the rate of removal of flocculent particles depends on tank surface area as well as depth. Some of the operational factors that will influence settling tank efficiency are recycling rate of wastewater, carryover of grit and screening from pretreatment, and the sludge pumping rate.

Clarifiers are usually divided into four zones. The inlet zone distributes the flow equally over the width or circumference of the tank, the settling zone occupies the bulk of the tank volume, and should be kept free of interference from the other three zones. The outlet zone consists of a series of weirs that allow the clarified water to leave at a low velocity so as to keep the settling zone quiescent. The sludge zone collects the settled sludge and allows for its removal with minimum disturbance.

All clarifiers, regardless of shape, must have a means of collecting and removing the settled solids and floating scum. Rectangular clarifiers usually have flights attached to endless chains. Floating grease and scum are conveyed to the scum trough and the settled sludge is moved to the sludge hopper. The sludge is then periodically pumped from the hopper to the sludge dewatering plant.

In circular clarifiers, scrapers attached to a rotating arm move slowly around the bottom of the tank. The scraper push the settled sludge towards the centre and into the sludge hopper, where it is pumped to the sludge handling facilities. The floating scum is removed by a skimmer and emptied into a scum trough. The skimmer is also attached to a rotating arm.

The clarified effluent flows out of the tank by passing slowly over a weir. The weir is usually located at the outer peripheral of a circular clarifier and at the end of a rectangular clarifier. The weir must be long enough to allow the treated water to leave at a low velocity.

Two steps must be completed to remove colloidal suspended solids from wastewater. Coagulation is the first step in liquid/solid separation. This process is accomplished by the addition of charged short-chained organic or inorganic molecules, which attract opposite charged suspended solids to neutralize the surface charges. The next step is flocculation which is agglomeration by particle bridging and is accomplished by adding long-chained organic molecules.

Microflocs, or pin flocs, formed during the coagulation process, are adsorbed onto the surface of the polyelectrolyte which have higher molecular weights. Each polymer molecule is therefore capable of colliding with and adsorbing many microflocs, and bridging them into large and rapidly settling macroflocs. The principal operational controls for secondary clarifiers serving activated sludge system include the return activated sludge (RAS) rate, the mixed liquor total suspended solids, and the sludge thickness level.

As an example of the diagnosis of operational problems, a decrease in clarifier efficiency is usually indicated by an increase in overflow suspended solids. Since a clarifier usually has a retention time of several hours, a trained operator often observes the water at the top of the clarifier; any increase in suspended solids on the water surface and flowing over the weirs usually indicate a decrease in clarifier efficiency in settling the solids.

In cases where polymers are used to improve the effluent clarity and increase solids settling rate, the plant operator can easily monitor and optimize his chemical treatment program by running a series of jar tests [MOP/11, 1976].

2.2.5 Factors Affecting the Activated Sludge Process

For a dynamic system such as wastewater treatment based on the activated sludge process, there are many factors that can affect the proper operation and efficiency of the process. These factors and their associated operational problems are discussed below.

Sludge bulking is one of the major operational challenges associated with the activated sludge process. When bulking occurs, the sludge becomes difficult to settle and as a result may be discharged in the effluent. This causes a deterioration of effluent quality, as well as a considerable loss of sludge from the system. Sludge bulking is usually associated with the presence of excess filamentous bacteria, and is known to be caused by other factors such as organic overloading, under-aeration and shock loading.

Besides reducing BOD by carbonaceous oxidation and assimilation, stringent regulatory limits on oxidized nitrogen requires the wastewater treatment plant to reduce the ammonia concentration. Basically, the biological oxidation of ammonia called nitrification is carried out in two stages by specific autotropic bacteria: Nitrosomonas which oxidizes ammonia to nitrite and Nitrobacter which oxidizes the nitrite to nitrate. The kinetics of the process is described in detail in standard wastewater texts such as Curds and Hawkes [1983].

Nitrification can be affected by a number of factors: dissolved oxygen (DO) level, pH, presence of inhibitors, and to some extend temperature. It has been suggested that for carbonaceous oxidation, the concentration of DO in the mixed liquor should not be less than 0.5 mg O_2 l^{-1} and for nitrification should not be less than 2 mg O_2 l^{-1}. The optimum pH ranges from 7.5 to 8.5 [Painter, 1978]. There is a proportional increase in nitrifying organisms with increase in temperature; however, due to interaction of other factors, the full effect of temperature change does not always occur. Cyanide, thiourea, thioacetamide, chlorates and other metallic salts are known to be inhibitory to the Nitrifying bacteria.

Denitrification occurs under anoxic (or oxygen deficient) condition. The facultative bacteria are able to make use of the nitrate as the H (hydrogen) acceptor in respiration. In the process, the nitrate is progressively reduced to molecular nitrogen ($NO_3 \rightarrow NO_2 \rightarrow NO \rightarrow N_20 \rightarrow N_2\uparrow$). which is relatively unavailable to most organisms and which may escape as gas to the atmosphere. This method of nitrogen stripping is effective only if full nitrification has occurred. The presence of oxygen could inhibit the denitrification process. In addition, the presence of excess denitrifying bacteria such as *Micrococcus*, *Pseudomonas* and *Achrombacter* can cause 'rising sludge' in the clarifier, when the nitrogen gas released by the bacteria bouys up the sludge flocs to overflow with the effluent [Curds and Hawkes, 1983].

Rising sludge could eventually lead to a situation where excess solids are flowing over the weirs of clarifiers. This will seriously affect the effluent quality of the clarifier. In addition, short-circuiting of flow through the clarifier, the presence of excessive suspended particles such as pin flocs and poor settlement of sludge could also cause such a situation.

Excessive foam generated during the activated sludge process can be attributed to the presence of a type of filamentous bacteria called Nocardia in the floc [Richards et al, 1990] or excessive surfactant contained in the influent wastewater.

The efficiency of the activated sludge process can also be affected by the nature of the influent waste water being treated [Mazurczyk and Smith, 1983]. This may affect the biological activity of the sludge and the sludge settling characteristics [Keinath, 1985]. For example, industrial waste water usually contains more toxic or inhibitory substances than sewage from homes (or technically referred as domestic waste water).

The presence of toxic or inhibitory substances will usually affect the metabolic activity of the activated sludge process although the sludge may become acclimatized to low levels of such substances if they are constantly present.

Specific wastes, such as carbohydrates, in the influent waste water may encourage filamentous growth in the sludge, which can result in poor settling of the flocs. The concentration of the organic matter, especially if the strength is fluctuating, can also affect the sludge characteristics.

Changes in the hydraulic loading, such as shock loads received from sewer as a result of heavy rain or from the return of supernatant liquors of sludge digestion plant, can also reduce the detention time and increase the chances of short-circuiting. [Crosby, 1984].

All the above essential information on symptoms and causes in activated sludge process that occur in the aeration basin and especially in the clarifier were transformed into inference diagrams for CLAR_EX as shown in Appendix A. They were then combined to form a Bayesian Belief Network known as CLAR_NET which form an essential product of the research work here.

2.3 Artificial Intelligence and Expert Systems

2.3.1 Introduction

Artificial Intelligence concerns with several areas relating to the simulation of human intelligence in a computing machine. It bridges many fields of study such as psychology, philosophy of mind, linguistic, neuroscience, logic and computer science. Some of the better known areas of Artificial Intelligence include natural language translation, speech understanding, machine vision, robotics, and expert systems.

Feigenbaum [1985] stated that there are two branches of Artificial Intelligence research: intelligent machines and cognitive science. Cognitive science studies human intelligence in its ability to perceive, learn, diagnose, analyse, solve problems and perform other activities. The intelligent machines approach tries to produce computer programs that can perform in a way which is considered as intelligent by human beings.

An expert system is a branch of Artificial Intelligence. An expert system can be defined as a computer program that has built into it the knowledge and capability which allows it to operate at an expert's level [Feigenbaum and McCorduck, 1983].

An expert system usually exhibits the following characteristics:

a) the domain knowledge and control knowledge are implemented separately;
b) the knowledge used to solve the problem can be expressed in primary symbolic terms rather than in numerical terms;
c) the implementation of the expert system results in representation of the knowledge and the process that uses the knowledge; and
d) it contains human expertise and judgement through the use of heuristics, or rules of thumb, and "compiled" knowledge. Compiled knowledge includes information which may have its origins in basic principles, and is therefore closer to experimental knowledge.

2.3.2 Historical Development

Alan Turing, who wrote a paper which suggested the possibility that machines could think, is considered as the initiator of Artificial Intelligence. He devised the "imitation game", known commonly as the Turing Test, to help explain his idea [Turing, 1964]. Artificial Intelligence only became a discipline of science in 1956, when John McCarthy first introduced the name at the Dartmouth Conference.

In the following years, research in Artificial Intelligence suffered a serious setback, due partly to a lack of understanding of how the human brain actually works and partly due to the scepticm about the "thinking machine". In 1974, the Lighthill Report in the United Kingdom concluded that there was no future in AI research, and recommended that all research funding in this area be terminated [Graham and Jones, 1988]. In spite of that, work on AI continued.

In 1983, there was a complete reversal of attitude towards AI. To a large extent, this was due to two main reasons; the first of which was the launching of the Japanese Fifth Generation Computer initiative. MITI of Japan funded pre-commercial cooperative research into the development of a Knowledge Information Processor - a fifth generation computer which focussed on handling of knowledge. Feigenbaum and McCorduck [1983] called this a "Japanese Challenge" and managed to galvanise the West into active research in Artificial Intelligence.

The second reason for this enormous interests in AI research in 1983 was the availablility of a few commercial applications in the form of "Expert Systems". These applications provided a general problem-solving paradigm suitable for applications in engineering, medicine, and other specialised fields.

To date, expert systems have been applied and implemented in virtually every field of knowledge. Some systems have been designed as research tools while others fulfill important industrial and business functions [Giarratano and Riley, 1989]. Some of the "classic" expert systems produced were MYCIN, DENDRAL, XCON, PROSPECTOR, and MACSYMA [Hayes-Roth et al, 1983]. MYCIN was designed to assist physicians in the antimicrobial treatment of patients, DENDRAL analyses mass spectrographic, nuclear magnetic resonance, and other chemical experimental data to infer the plausible structures of unknown chemical compounds. XCON is an expert configuring system for DEC computer systems and has saved DEC millions of dollars a year by reducing the time to configure an order and to improve the accuracy of an order. PROSPECTOR, which was developed to interpret geological data for minerals, has successfully discovered a molybdenum deposit whose ultimate value will probably exceed $100 million. MACSYMA has achieved a high level of competence in the symbolic computations associated with applied analysis.

There are major successes with the commercial application of expert systems in industries recently. The LDS Hospital in Salt Lake city in United States has installed a complex expert system called HELP (Health Evaluation through Logical Process) to assist physicians in selecting the best antibiotics for their patients [Betts, 1994]. An expert system was developed in 1994 for Campbell Soup Company to reduce the equipment downtime from days to hours only, thus improves the productivity. General Motors Company launched the Expert System Scheduling (ESS) to capture the experience of human schedulers for most of the decisions involved in scheduling of the production. Lubrizol Corporation, a specialty chemical company, satisfied a legal requirement in the United States to provide information about the constituents and handling of its chemicals to the customers through an expert system called MSDS [I/S Analyzer Case Studies, 1995]. General Electric Power Generation, Inc. applied expert-system technology to maximize operating revenue for its power generating plants by optimizing output and heat rates and reducing maintenance expenses [Deitz, 1995].

2.3.3 The Development of an Expert System

The development of a non-trivial expert system can be a rather time-consuming task. A sophisticated system may require a team of several people working together over a period of several years [Mishkoff, 1988]. There are usually three categories of people involved in the development of an expert system: the knowledge engineers, domain experts, and the end-users.

A knowledge engineer is an individual who is competent in developing expert systems [McGraw and Harrison-Briggs, 1989]. He or she assumes the tasks similar to those carried out by system analysts, these include: analysing information flow, determining program structure, working with domain experts to obtain information, and performing design functions. In order to acquire necessary knowledge, the knowledge engineer should have some mastery of the domain and be able to identify the type of knowledge that is required. In addition, the knowledge engineer should be able to conceptualise and analyse the domain, its concepts and interrelationships, and able to communicate effectively with the domain experts.

A domain expert is an individual who has significant expertise in the domain of the expert system being developed. Domain experts are often retiring "sole sources" of information whose expertise companies wish to preserve. In other cases, multiple domain experts may be required to offer expertise that can be combined and shared among the less expert workers. In general, a domain expert chosen for the expert system development should possess the following characteristics: substantial knowledge and experience in the domain, an ability to explain important concepts and heuristics, an ability to communicate effectively, and to be introspect and patient. The knowledge engineer and the domain expert usually work very closely together for long periods of time throughout the several stages of the development process [Henrion et al., 1991].

In the process of refining the initial expert system prototype, it would be beneficial if the intended end-users can participate in reviewing the prototype. This would usually help the knowledge engineer in fine-tuning the prototype to the best possible form.

The process involved in building the expert system can be divided into five distinct steps [Hayes-Roth et al., 1983]. These five steps are: identification, conceptualization, formalization, implementation, and testing.

Identification is the first stage in which the important stages of the problem are characterised and goals are set for the entire project. During this stage, the participants, exact nature of the problems, resources available, intended goals, and deadline for completion of the prototype should be clearly identified.

In the conceptualization stage, the knowledge engineer may create a diagram of the problem to depict graphically the key relationships between the objects and the processes in the problem domain [Graham and Jones, 1988]. As in the identification stage, the conceptualization stage involves a circular procedure of iteration and reiteration between the knowledge engineer and the domain expert. This stage is complete when both have agreed that the key concepts and the relationships between them have been adequately conceptualized.

Formalization involves mapping the recognized concepts, subtasks, relations, and other information into a particular set of schemes. During this stage, the knowledge engineer should be familiar with the following details: the various techniques of knowledge representation and heuristic search used in expert system, the expert system "tools" that can greatly expedite the development process, and other expert systems that may solve similar problems and thus may be adaptable to the problem at hand. This is often the most interactive stage of expert system development, and thus most time consuming [Harmon and King, 1985]. The knowledge engineer must develop a set of rules and ask the domain expert if those rules adequately represent the expert's knowledge. As in other stages, this process is iterative: the rule review is repeated and the rules are refined until the results are satisfactory.

During the implementation stage, the formalized concepts are encoded into a computer, using the techniques and tools chosen for the implementation of the first prototype of the expert system. Once the prototype has been refined sufficiently to allow it to be executed, the expert system is ready to be tested thoroughly to ensure that it executes smoothly. The final stage of testing requires the prototype system be evaluated to ensure that the basic assumptions, knowledge, heuristics, and rules are accurate. During or after the testing stage, feedback loops are implemented so that further refinement or complete reformulation of the prototype is made. McGraw and Harrison-Briggs [1989] described the above process in greater detail.

2.3.4 Knowledge Representation

Some of the methods of representing knowledge were developed from observing how humans in general cope with the problem of representing and organizing knowledge. The human mind, like a computer, faces the problem of storing and retrieving knowledge from its memory [Buchanan and Feigenbaum, 1978]. In general, the main types of knowledge representation are network-based, logic-based, and rule-based systems.

Although semantic networks provided one of the earliest approaches to knowledge representation, they introduced a number of important concepts, such as inheritance of properties, which are still used in modern knowledge representation systems [Anderson and Bower, 1973]. In general, all approaches to semantic networks rely on two fundamental units:

a) nodes - which represent objects, concepts, or events, and

b) links - which represent relations between nodes.

In logic-based systems, knowledge is represented as assertions in logic. Normally, this form of representation is coupled with an inference procedure based on theorem proving. PROLOG is an example of a logic-based representation language.

Another approach to knowledge representation is based on production rules. In this approach, the domain knowledge is represented in the general form: IF <Antecedent> THEN <Consequent>. Since rules are a straight-forward method of knowledge representation, they provided an attractive means of building expert systems, and were successfully used to construct MYCIN and DENDRAL [Shortcliffe, 1976].

Other knowledge representation methods were also developed independently. Frames are highly organized data structures, much like a record in the Pascal programming language [Minsky, 1975]. A frame is usually used to represent an object (which is a term referring to some convenient package of information), such as a physical thing like pen, cup or an abstract entity such as goals. Another interesting representation approach is based on the blackboard model. This model was initially developed for HEARSAY-II speech understanding system [Erman, 1980]. When this model is used in an expert system context, each participating expert is called a knowledge source. A knowledge source need not be a human expert, but may be a knowledge-base devoted to performing a specific task. The blackboard then becomes a way of sharing hypotheses and information among the knowledge sources.

2.3.5 Inference Mechanism

Inference is the process of combining facts and rules to produce a structure of knowledge. It can be viewed as a tree of possibilities. This provides a diagrammatic way of representing the structure of knowledge and helps in visualizing inference as a dynamic process [Parsaye and Chignell, 1985].

Since each rule consists of a premise and a conclusion, a tree can be constructed whose nodes are the clauses used in the rule and whose branches are arrows connecting the clauses. When clauses are joined by an AND connective, we have an "AND node"; while clauses joined with the OR connective have an "OR node". The branching in each tree reflects the structure of a set of rules. Such trees are called AND/OR trees. [Giarratano and Riley, 1989].

Different methods of inference traverse the tree in different orders, although the same proof tree may be produced. There are two most common inference methods used in expert systems, they are forward chaining and backward chaining. The term chain refers to a group of multiple inferences that connect a problem with its solution.

Forward chaining is also known as data-driven or antecedent-driven reasoning. The system starts from an initial state of known facts and moves towards a goal or conclusion. In the case of the tree structure described above, forward chaining starts from the leaves and works towards the roots until a chain of branches that leads to the intended goal is found [Parsaye and Chignell, 1985]. When this system is applied in expert systems, all the rules are tested and those rules whose antecedents are shown to be true are then fired. Data is then generated, and more rules are then tested and fired. The process continues iteratively until no more rules are fired. This process is most useful when there are many hypotheses and few input data. Its disadvantage is that it may be time-consuming to check all the facts as some of them are irrelevant.

Backward chaining is goal-driven or hypothesis-driven reasoning. A system uses the backward-chaining mechanism if it starts by assuming a goal or hypothesis and then reasons back to known data or facts to support or discount the assumed hypothesis. This is a reversal of the forward-chaining process in the tree structure where the root is the starting point and the branches are followed towards the leaves until the goal is found [Parsaye and Chignell, 1985]. In applying this mechanism to expert systems, the knowledge base of rules which might give the desired solution is searched first, then the rule antecedents are searched to see what needs to be known to fire the rule. During this process, the rule which is being worked on is put aside and stacked and a sub-goal for proving the antecedent of the rule is set-up. The knowledge base is then searched for rules to prove the sub-goal. Once again the search of antecedents and stacking of rules are repeated until there is no rule to prove the sub-goal. Then the user will be asked to provide a value until the rule is satisfied and the hypothesis is proven.

Another common inference mechanism is mixed chaining whereby a system combines both the forward-chaining and backward-chaining strategies [Graham and Jones, 1988]. The system starts with initial state of known facts to assign a probability to each of the potential goals. It then sets up sub-goals and requests more information when necessary until the intended goal is achieved. The advantage of this strategy is that the user is required to input only relevant data to the problem at hand, and if an initial hypothesis is disproved, then the next assumption is made according to the current information.

2.3.6 Reasoning Under Uncertainty

Uncertainty is considered as a lack of adequate information to make a decision. Human beings live in an uncertain world and decisions are commonly made in the face of this uncertainty. Financial investment decisions, medical therapies, engineering judgments and the like are constantly being made, although the information that leads to each decision and outcome may be uncertain. As such, expert systems developed to emulate human experience should have the capability to reason under uncertainties and to make decisions based on available information [Parsaye and Chignell , 1985].

While there are many applications of expert systems which can be achieved using exact reasoning, many others require inexact reasoning using uncertain facts or rules. Some include classic expert systems that have successfully dealt with uncertainty include MYCIN for medical diagnosis and PROSPECTOR for mineral exploration [Giarratano and Riley, 1989]. Both of these systems arrive at conclusions even when not all the conclusive evidence is known. In the case of MYCIN, this is necessary because a delay in treatment for more tests may add considerable cost and the patient may die in the mean time. Similarly, the cost factor also applies to mineral exploration. It may be cost effective to start drilling when there is a 95% certainty of success than to spend hundreds of thousands of dollars to be 98% certain.

There are many types of error that can contribute to uncertainty. Errors can be classed as: ambiguous, incomplete, incorrect, measurement, random, systematic, and reasoning. Each of these classes can be sub-classified under possible causes of error such as human error, false positive, and equipment malfunction. Giarratano and Riley [1989] described these and other errors in detail.

Expert systems may consist of deductive and inductive rules, where the inductive rules are of a heuristic nature. A heuristic is also known as a 'rule of thumb' because it is based on the experience of human experts. Human experts have a distinct characteristic of reasoning well and making good decisions under uncertainty, often under a great deal of uncertainty, otherwise they are not considered experts for long. In addition, human experts can easily revise their judgment if some of the original facts are later found to be wrong - a process known as non-monotomic reasoning.

There are a number of methods of reasoning under uncertainty which can be incorporated into expert systems. These include fuzzy logic, certainty factors, Dempster-Shafer Theory, and Bayes' Theorem.

2.3.6.1 Fuzzy Logic

Fuzzy logic was introduced in the mid-1960s as an alternative to binary logic and probability theory by offering alternatives to traditional notions of set members and logic [Zadeh, 1965]. It has recently been applied to some home electrical appliances, as well as in other areas such as forecasting short-term load in a power generating plant [Hsu and Ho, 1992], and in rubber compounding [Kobalicek *et al*, 1993].

Fuzzy logic is an extension of Boolean logic into the domain of real numbers. In Boolean Algebra, the truth values are indicated by a value in of 0 to 1, where 0 represents absolute false and 1 represents absolute true. Fuzzy logic extends this concept by allowing intermediate values such as 0.9 which means 90 percent true or 10 percent false.

Fuzzy logic deals with the laws of inference for fuzzy sets [Zadeh, 1984]. There is little agreement among Artificial Intelligence researchers on the use of these modified logic for intelligent systems or for reasoning with incomplete data[Hayes-Roth et al, 1983].

Consider the statement: Mary is old. If Mary is 70 years old, we may assign a certainty of 0.90. The statement could be translated into set terminology as: Mary is a member of the set of old people. In the notation of fuzzy logic, this is written as: mOLD(Mary) = 0.90, where m is the membership function for the fuzzy set of old people (denoted OLD) which returns a value between 0 and 1.

This is contained in the fundamental equation for fuzzy sets. If X is a collection of objects (a universal set), then a fuzzy set A in X is defined to be a set of ordered pairs, such that:

$$A = \{[x, \mu_A(x)|x \in X\} \tag{2.1}$$

where, $\mu_A(x)$ is called the membership function of x in A. Details of the fuzzy set functions and their derivations are described in Zadeh [1984].

There is a distinct difference between fuzzy logic and probability although both operate on an equivalent numeric range. In the probabilistic approach, the above statement is read in natural language as: there is a 90 percent chance that Mary is old; while the same statement in fuzzy logic means: Mary's degree of membership within the set of old people is 0.90.

Fuzzy sets theory provides a means for approximate or semi-qualitative reasoning. However, this also means that it is a fairly weak form of plausible reasoning, in the sense that it does not allow any reinforcement of evidences and updating of beliefs. However, fuzzy sets applied in rule-based expert systems has the advantage of less computational overhead.

2.3.6.2 Certainty Factors

Another technique of dealing with uncertainties is through the use of certainty factors, which were formalised during the development of MYCIN expert system [Shortliffe, 1976]. MYCIN was designed to assist physicians in the antimicrobial treatment of patients with serious infections such as bacteremia and meningitis.

A certainty factor represents a degree of truth, or confidence factor (CF), which is a number ranging from -1 for absolute false to +1 for absolute true. It can also be taken to range from -10 to +10 or -100 to +100. The certainty factors are not probabilities and the degrees of truth of all statements in a given context do not need to sum up to the maximum number within the number range.

The certainty factor formalism makes use of the concept of measures of belief (MB), measure of disbelief (MD), and composite Certainty Factor (CF) [Krause and Clark, 1993]. In the MYCIN expert system for medical diagnosis, the degree of confirmation was originally defined as the certainty factor, which is the difference between belief and disbelief as:

$$CF = MB - MD \tag{2.2}$$

where, CF is the certainty factor in the hypothesis h due to evidence e.

MB is the measure of belief in H due to e, and is defined as the increase in the probability of the hypothesis provided by the observation of evidence e, divided by the current disbelief, 1-p(h). So that,

$$MB = \frac{(p(h \mid e) - p(h)}{(1 - p(h))} \tag{2.3}$$

MD is the measure of disbelief, which is equal to the decrease in belief, p(h)-p(h|e), divided by the current belief, p(h), as:

$$MD = \frac{(p(h) - p(h \mid e))}{p(h)} \tag{2.4}$$

A problem encountered in using Equation (2.2) is that under some circumstances, a single piece of negative evidence could outweigh the impact of several pieces of evidence. As such, in subsequent applications such as EMYCIN [van Melle et al, 1984], the definition of CFs was changed to:

$$CF = \frac{(MB - MD)}{1 - \min(MB, MD)} \tag{2.5}$$

In MYCIN, the rule antecedent is considered as true only if the CF is greater than the threshold value of 0.2. This threshold value is an ad hoc way of minimizing the activation of rules which only weakly suggest a hypothesis. Without a threshold, many rules may be activated with little or no value, thus reducing the system's efficiency.

Krause and Clark [1993] mentioned that the combined CF for a set of rules with certainties factors are made according to one of the three combination functions:

- an *antecedent pooling function* which determines a pooled CF for the set of antecedents in a rule. As such, for a conjunctive set of premises, the pooled MD is the individual maximum MD, and the pooled MB is the individual minimum MB, and so the combined CF would be the minimum of the CFs.

- a *serial rule combination* function that propagates CFs to the consequence of rules, such that,

  for $CF_{antecedent} > 0$, $CF_{consequent} = CF_{antecedent} \cdot CF_{rule}$ (2.6)

  for $CF_{antecedent} \leq 0$, $CF_{consequent} = 0,$

- a *parallel combination function* that combines the results from different rules when they relate to the same proposition,

  for CF1, CF2<0: $CF_{combine}(CF1,CF2) = CF1+CF2(1+CF1)$ (2.7).

  for CF2, CF2>0: $CF_{combine}(CF1,CF2) = CF1+CF2(1\text{-}CF1).$

  Otherwise: $CF_{combine}(CF1,CF2)=(CF1+CF2)/\{1\text{-}min(|CF1|,|CF2|)\}.$

The major advantage of CFs was the simple computation by which uncertainty can be propagated in the system. The CFs was easy to understand and clearly separated belief from disbelief [Giarratano and Riley, 1989].

However, there were limitations associated with using the CFs [Pearl, 1987]. Krause and Clark [1993] noted that in CF formalism, the assumption of semantic modularity (locality and detachment criteria) is untenable. This makes the approach inflexible, and means it can be used under highly circumscribed situations, such that:

- when all the rules are predictive or diagnostic, but not a mixture of both, and
- when all dependent evidence is lumped together in a single rule.

The other problem is that it suffers from the problem of correlated evidence. Adopting the example from Henrion [1991], suppose that three reports (say TV, radio, and a newspaper) of a disaster was received from three independent correspondents. Each report in isolation mentioned that thousands have died in the disaster. Then the resulting belief that thousands have died is justifiably higher than it would be from any one source in isolation (CF = 0.9375 if MB for each report = 0.5). However, if we discover that the reports were based on a single source of observation, then it is inappropriate to treat the three reports as independent. As such, unlike the Bayesian Belief Network system where the conditionally dependent hypotheses are arranged in cliques, the solution to overcome such problem in CFs is by having all rules to cover each possible situation. This would need 2^n number of rules to cover all the situations.

The above limitations of CFs, especially on the limitations of rule-based expert system to handle plausible reasoning, are explained in greater detail in Chapter 3 and by Chong and Walley [1996].

2.3.6.3 Dempster-Shafer Theory

This method of inexact reasoning originated from the work by Dempster [1967] who modelled uncertainty using a range of probabilities rather than using a single probabilistic number. Dempster's work was extended and refined by Shafer [1976] to form Dempster-Shafer Theory.

Unlike Certainty factors, the Dempster-Shafer Theory has a good theoretical foundation. It assumes that there exists a fixed set of mutually exclusive and exhaustive elements called the environment, such that q = (q1, q2, ... qn), where each q symbolises an environment with elements which are mutually exclusive but are of interest to a particular question. An example stated in Giarratano and Riley [1989] is:

$$q = (\text{airliner, bomber, fighter}) \qquad (2.6)$$

If the question is "What are the military aircrafts?", the answer is the subset of q:

$$(q2, q3) = (\text{bomber, fighter}) \qquad (2.7)$$

and likewise, the question "What is the civilian aircraft?", the answer is the subset of q:

$$(q1) = (\text{airliner}) \qquad (2.8)$$

Since the elements are mutually exclusive and the environment is exhaustive, there can be only one correct answer (a subset of q) to a question. An environment is called a frame of discernment when its elements may be interpreted as possible answers, and only one answer is correct.

A fundamental difference between Dempster-Shafer theory and probability theory is the treatment of ignorance (Shafer [1976]). In addition, it refers to the degree of belief in evidence as analogous to the mass of physical objects that can be moved around, split up or combined.

The general form of Dempster's Rule of Combination is:

$$m1 \oplus m2 = \frac{\sum m1(X)m2(Y)}{1-k} \tag{2.9}$$

where k is called the amount of evidential conflict (k=0 for complete compatibility and k=1 for complete contradiction) is given by:

$$k = \sum_{X \cap Y = 0} m1(X)m2(Y) \tag{2.10}$$

and m denotes mass of evidence.

The computational complexity of deriving the Dempster-Shafer Belief functions is described in detail by Provan [1990]. The limitations of the Dempster-Shafer Theory include the inability to closely model diagnositic reasoning, and to distinguish between uncertainty, or lack of sufficient knowledge, and indifference. Lingras and Wong [1990] illustrated a possible method of incorporating dependencies based on limited information.

2.3.6.4 Bayesian Probability and Bayesian Belief Networks

Bayesian probability is firmly founded in probability theory, and by far has the longest tradition among all the methods of handling probability and is the best understood [Krause and Clark, 1993].

The Bayesian rule of conditioning allows the updating of belief a hypothesis in response to the observation of evidence. The revised belief in hypothesis B on observing evidence A, P(B | A), is obtained by:

$$P(B|A) = \frac{P(A|B).P(B)}{P(A)} \tag{2.11}$$

where, P(A) and P(B) are the prior beliefs in A and B respectively, and $P(A \mid B)$ is the probability of A occurring given B is true. It should be noted that Equation (2.11) enables one to reverse the direction of reasoning from $P(B \mid A)$ to $P(A \mid B)$.

Taking a closer look at this approach, the conditional probability statement $P(B \mid A_1)=p_1$ means that if A_1 occurs and is the only evidence known to be relevant to outcome B, then probability p_1 can be attached to outcome B. If further evidence $(A_2,A_3,...,A_n)$ is observed, then $P(B)=p_1$ is no longer true and should be replaced by $P(B)=p_2$, where p_2 is the known or derived value of the conditional probability $P(B \mid A_1,A_2,A_3,....,A_n)$. In this approach, locality is not assumed. An item of evidence can only be ignored during the evaluation of P(B) if it is shown to be irrelevant to B.

In many classic rule-based expert system such as MYCIN and PROSPECTOR, uncertainty values are associated with the rules and combined using simple syntactic principles as the rules are fired. This approach to the handling of uncertainty is computationally efficient, but unless strong independence assumptions can legitimately be made, it is semantically sloppy as illustrated by Naepolitan [1990].

As discussed earlier, one of the major shortcomings of the Certainty Factor's approach in dealing with uncertainties lies in its inability to handle correlated evidence. This problem is largely overcome in using the BBN method [Krause and Clark, 1993]. Correlated evidence refer to two or more pieces of evidence which add support to a hypothesis. However, if they have been derived from a common source, the combined support they give to the hypothesis are not be as strong as that obtained as a situation where they are each an independent evidence. Such a condition can only be handled well by a rigorous probabilistic model.

The semantic approach taken in a rigorous probabilistic model is computationally intensive. This presents a major weakness in the earlier Bayesian approach, whereby a naive representation of a problem in a probabilistic framework would require the elicitation of a probability distribution function defined over all the propositions of interest. As such, a problem involving n propositions (A1, A2,..An) will require elicitation of 2^n such values.

However, the strong foundation of Bayesian probability motivated researchers like Pearl, Cheesman and Spiegelhater to develop methods based on graphical representation of dependencies with efficient updating algorithm to overcome computational overhead [Krause and Clark, 1993].

Such methods, known as Bayesian Belief Networks, or sometimes called Causal Networks, are based on directed acyclic graphs (DAG) with arcs to link *parent* nodes(causes) to *child* nodes(effects) to represent the causal relationship of these nodes. If the network has interconnecting nodes namely A to H as shown in Figure 2.4, then the joint distribution can be expressed as product of the nodes' conditional probabilities as:

$$P(A,B,C,D,E,F,G,H) = P(H|D,E)\cdot P(G|E)\cdot P(F|D)\cdot P(E|B,C)\cdot P(D|A)\cdot P(C|A)\cdot P(B)\cdot P(A) \tag{2.12}$$

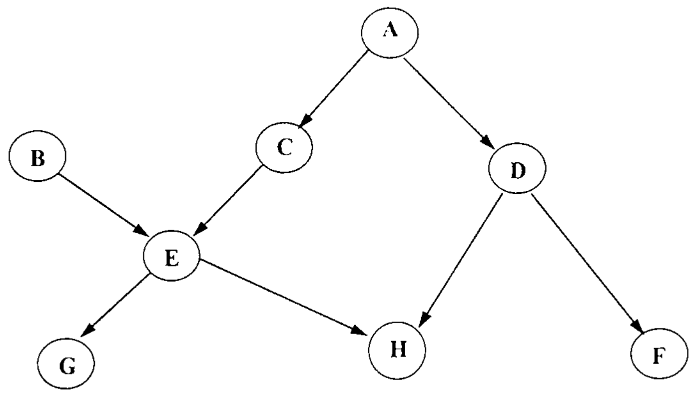

Figure 2.4 A Bayesian Belief Network with nodes and arcs

Charniak [1991] reported that Bayesian Networks have proven to be better than MYCIN-style certainty factors or Dempster-Shafer theory of belief. It allows the solution of probabilistic problems without the traditional hurdle of having to specify a set of numbers that grow exponentially with the complexity of the problem.

This method of propagating probabilities through graphical structures with an effective algorithm of updating beliefs led to the major part of the work in this project in developing an effective expert system to diagnose faults in activated sludge systems. The algorithm for this method is described in detail in Chapter 4.

According to published literature, the application of this method led to the development of MUNIN (for Muscle and Nerve Inference Network), an expert system designed to assist the diagnosis of associated neuro-muscular disorder [Andreassen et al, 1987; Jensen et al., 1987]. The technology underlying MUNIN was refined and has been developed into a commercial expert system shell called HUGIN.

Spiegelhalter and Lauritzen[1990] refined the technique and developed an expert system to assist in the diagnosis of the congenital heart disease in children - a sickness that can cause cyanosis ("blue babies") or heart failure and death if not treated in time. A graphical network for diagnosis was constructed in collaboration with the pediatric cardiologists at the Great Ormond Street Hospital for Sick Children in England. Results from the expert system showed a general agreement with experts' prediction.

Sarkar and Murthy [1995] attempted to set criteria to evaluate approximate belief network representations for expert system. Heckerman [1990] and Pearl [1996] discussed the use of Bayesian Belief Network for troubleshooting problems. The application of the method to a subsystem of a typical wastewater treatment plant has been described by Chong and Walley [1996]. This will be presented in detail in subsequent chapters.

It should be noted that the BBN is fundamentally concerned with the structure of reasoning; not merely with the numerical coefficients themselves. The essence of relevance is identified with a structure of network depicting the causal relationship between the nodes. The use of probability theory in BBN is aimed only in providing a coherent account of how belief should change in light of partial or uncertain information.

As Pearl [1988] puts it, "probability is not really about numbers, it is about the structure of reasoning".

2.4 The Application of Expert Systems in Wastewater Engineering

The major emphasis of published work on the application of expert systems, or any branches of artificial intelligence, in wastewater treatment focuses on the activated sludge process. Gall and Patry [1989] noted that Beck et al. [1978] were among the first to make use of expert system-type rules for wastewater treatment plant operation and control. Though the authors did not name the program as an expert system, they did employ an important aspect of expert systems, human expertise. The system includes twenty heuristic control rules, and fuzzy logic provides qualitative interpretation of the quantitative data. The full potential of applying expert systems in activated sludge plant was initially discussed by Horan and Eccles [1989]. Chong et al. [1991] covered the potential application of expert systems to the unit operations and processes of wastewater treatment systems.

A prototype expert system which emphasized the representation of the uncertainties that exist between symptoms, diagnosis, and responses was developed by Johnston [1985]. His system dealt with the effects on treatment performance of toxic substances in a wastewater treatment plant's inflow. To allow for these uncertainties, fuzzy relations were chosen to form the basis for the knowledge base. Meeda [1985] also reported the development of an expert system for the diagnosis of faults in the activated sludge process.

Gaselbracht et al.[1986] applied expert system techniques to evaluate activated sludge systems for sludge bulking potential. The core of his report centres on the rule structure details and the calibration of uncertainties in evidence and rules.
In 1987, Jenkins and Jowitt applied Beck's rules to develop a simple expert system in PROLOG for the diagnosis of problems in an activated sludge plant. Berthouex et al. [1987] extended Beck's work by integrating the expert system to a database to provide plant operators with a more powerful software package. An interesting feature of Berthouex's work is that the system can be customized to a specific treatment process.

The potential applications of expert systems in dynamic modeling of specific wastewater treatment processes were suggested by Rittman [1989], Chapman et al. [1989] and Andrews [1989]. Beck [1989] discussed in detail the system identification and problems in dynamic modeling, in particular with respect to wastewater treatment and the receiving water body.

A rule-based expert system for the diagnosis of faults in the activated sludge process and the identification of remedial actions, referred to as DASP (Diagnosis of the Activated Sludge Process), was developed by Gall and Patry [1989]. The knowledge base was encoded using Personal Consultant Plus (Texas Instruments) and tested under actual plant operating conditions. The authors recognized the difficulty of assessing the true potential benefits of this technology to wastewater treatment plant operation and control, and emphasized that the operational benefits of a knowledge-base system depended largely on the continuing contributions from plant operators.

Chan and Koe [1991] studied and developed a prototype expert system to diagnose sludge bulking problem in the activated sludge process of wastewater treatment system. The knowledge in the prototype was compared with the conclusions of a panel of human experts in a wide range of operating conditions, and was reported to be in good agreement.

Laukkanen and Pursiainen [1991] developed an expert system for two biological wastewater treatment facilities in Finland and transferred them into process automation. Hale [1991] also mentioned that an expert system was implemented at a conventional activated sludge treatment facility in the United States to assist operators in process control. Both papers reported that the expert systems have improved the daily operation of the wastewater treatment plant and have lessened dependence on timely laboratory results to make process control decisions.

An integrated data management and operational process control system along with diagnostic and predictive expert systems was developed by Stover and Campana [1991] to assist in the operation of wastewater treatment plants. The computer program stores and analyzes plant operational data, and generates any reports required for documentation. It also contains bio-kinetic process control equations and analysis to provide daily operational strategies. The paper reported that this system has been successfully employed at several biological wastewater treatment plants.

Recently published work has seen the application of expert system to the optimum selection of sludge dewatering process, whereby the life cycle costing model is also included to determine the least cost dewatering process and the optimum polymer dosage [Elimam and Dodin, 1994]. A computer graphics system called CRT has also been developed whereby treatment plant operators can move through the entire plant and view the equipment or unit process status on the computer screen [Valorose, 1994]. Neural networks, a branch of artificial intelligence, has been used to predict the performance of a municipal treatment plant using the trickling filter system [Pu and Hung, 1995].

Substantial interests and development in mathematical models on wastewater treatment system were noted. Speitel and Hughes [1982] examined the mathematical modeling of the activated sludge process using two approaches, one from the standpoint of a unit process and the other as an integral component of plantwide mass balance models. Both approaches were compared to an actual wastewater treatment plant. Nieuwstad and vantHofl [1986] used three mathematical models to simulate the sludge acclimation process in degrading nitrilotriacetic acid (NTA) in activated sludge systems. The results showed that the average removal at fluctuating concentrations decreases with increasing sludge loading, which was well within the acceptable range of the experimental value. New settling velocity models for secondary settlers of the activated sludge systems were designed by Cho et al. [1993]. These models incorporated the slurry viscosity term, and the results were found to be in good general agreement with experimental data.

Gujer and Larsen [1995] developed the Activated Sludge Simulation Model (ASIM) as a design tool to study the simulation of the dynamic behaviour of nutrient removal in the activated sludge system. The model has a user interface which is simple to use in the classroom, and is also good enough for professional design work. ASIM was modified by Fougias and Forster [1995] and the modified version allowed the effect of enrichment of the substrate in activated sludge system to be examined. The model showed the interfacial substrate enrichment did enhance filamental growth which confirmed earlier hypothesis. The process simulation over a range of sludge ages showed that its effect was less pronounced as the sludge age was reduced.

A simulation model for handling organic waste system, ORWARE (Organic Waste Research) was constructed by Dalemo et al. [1997] which provided a comprehensive view of the environmental effects, plant nutrient utilization and energy turnover for such system. This model can be used to simulate different scenarios, with the results presented as the gross figure for the entire system and for each process in terms of emissions to air and water, energy turnover and the amount of residues returned to arable land.

It is evident that, though a significant number of expert systems have been developed in wastewater treatment, the main bulk of work has been concentrated on application of rule-based expert systems. In particular, there should have been more work in the expert systems area on the dynamic modelling of the wastewater treatment plant though such models have the potential to simulate the actual operating conditions of the plant.

These expert systems developed so far, being rule-based, will be limited in their capabilities due to the inherent weaknesses in the rule-based approach, such as its inability to reason both diagnostically and predictively. As mentioned earlier the ability to reason bi-directionally is central to the production of a correct diagnosis.

CHAPTER 3 DEVELOPMENT OF THE DIAGNOSTIC MODEL FOR CLARIFIERS

3.1 Introduction

It was initially envisaged a rule-based expert system would satisfy the goal of developing an expert system to diagnose faults in clarifiers. Thus, considerable effort was put into the development of inference diagrams, which depict graphically the connection of each major observable symptom with its most likely causes. A working prototype expert system, CLAR_EX, was developed based on the inference diagrams developed in this work.

However, in the subsequent stages of refining CLAR_EX to handle uncertainties, considerable challenges were encountered in shaping CLAR_EX into an "expert". The 'thought process' of CLAR_EX was based on the inference diagrams, each with a symptom linking to possible causes; which in an actual situation could have a possible cause or causes resulting in a number of symptoms, or a symptom which in turn causes other symptoms to occur. In addition, in an actual wastewater treatment process having several operating parameters, any new evidence should cause a change in belief that other symptoms would or would not occur. Only by this means could CLAR_EX be designed to ask questions of the user which were relevant to the diagnosis as it progressed. In drawing up the inference diagrams, the interconnected relationships between the symptoms had not been derived. Thus the CLAR_EX prototype tended to ask a lot of unrelated questions. Consequently, a substantial revision of the system was clearly necessary. However, this presented serious problems because of the need to reason both predictively and diagnostically in a dynamic way - two processes which are difficult to achieve using rule-based methods.

Fortunately, the research took a major step forward in finding a solution to this problem when the author became aware of the Bayesian Belief Network (BBN). This technique, which uses the Trees of Clique Method developed by Lauritzen and Spiegelhalter [1988], was subsequently adopted. The first major task was the development of a single belief network to link all the relevant entities (causes and symptoms) described in the 21 inference diagrams.

The belief network, CLAR_NET, was developed. The process involved two major tasks: the development of an accurate structure, and the elicitation/derivation of the conditional probabilities for each node. The first step in developing the network structure involves combining all the essential features of the inference diagrams into a single belief network. Since the network basically involved "parent" and "child" nodes, considerable challenges were encountered and efforts made in defining the "family relationship", that is, who were the "parents" of which "children". (A "parent" node refers to a node preceding a "child" node in the network, both nodes are connected by an arc from the former to the latter node). It is rather easy to argue that there are several ways to define "parents" and "children" in wastewater operation, and the work here attempted to distinguish them as appropriately as possible.

The other portion of the network was done by incorporating appropriate prior or conditional probabilities into each belief node as the case required. The network then underwent several cycles of testing, verification by domain experts and modification to fine tune the probabilities. It should be noted that this network represents an example of applying the Bayesian Belief Network approach to a typical activated sludge system. Since there can be a multitude of configurations of wastewater treatment systems, the work here does not claim to represent or solve all problems in activated sludge systems.

The above summarised all the essential steps in the development process, which is shown diagramatically as a flow chart in Figure 3.1. The remainder of this chapter will describe the development of CLAR_EX, and the limitations associated with the system in handling uncertainties. Chapter 4 details the concepts and algorithm behind BBNs to enable understanding of its use here in the development of CLAR_NET, a BBN replacing CLAR_EX. The development process of CLAR_NET is described in detail in Chapter 5.

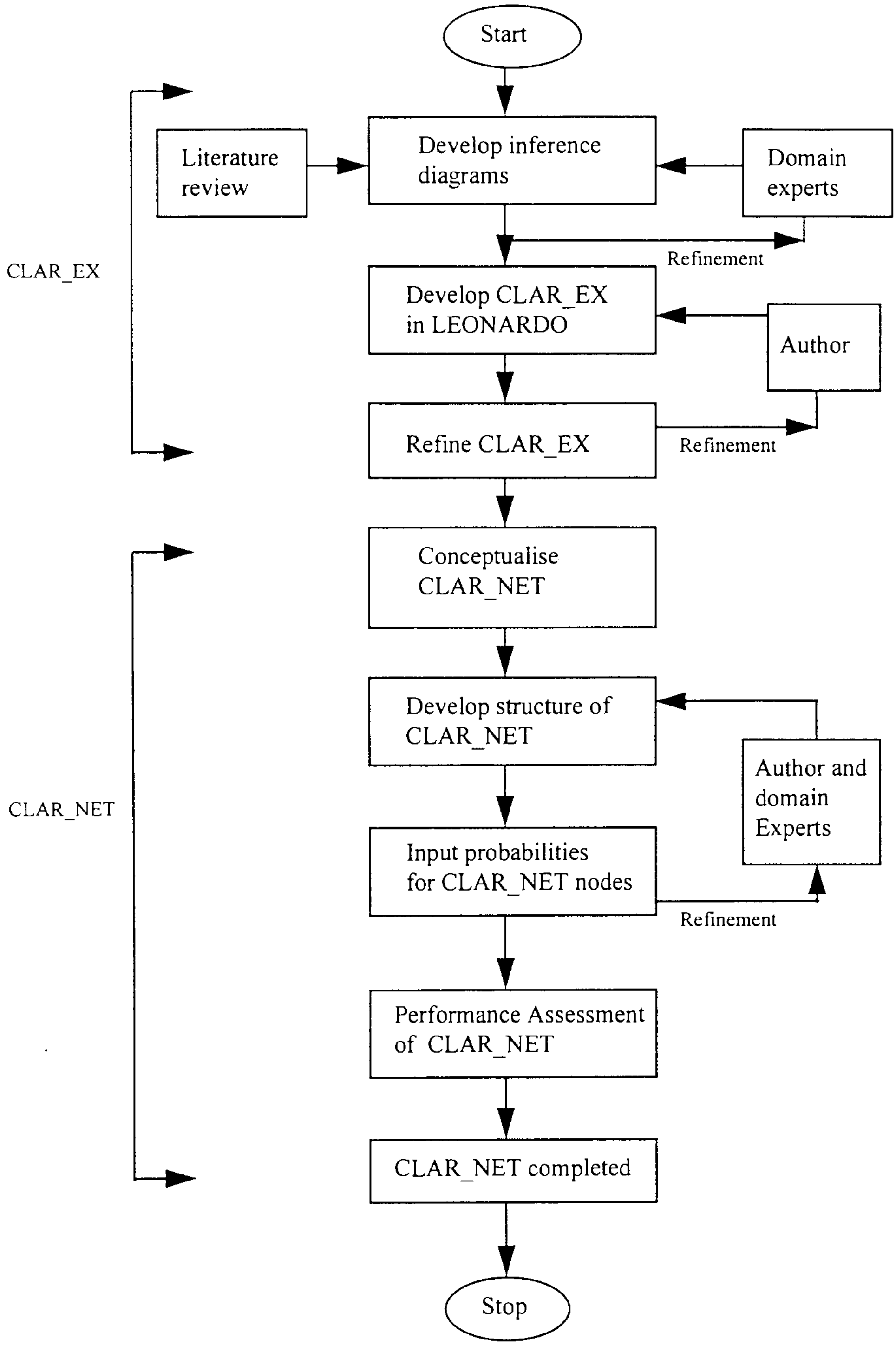

Figure 3.1 A flow diagram summarising the major development stages for this research work.

3.2 Development of CLAR_EX

The development of the CLAR_EX prototype consisted of 3 major steps:

a. development and refinement of inference diagrams for the diagnosis and correction of clarifier problems;
b. learning to use the LEONARDO expert system shell; and,
c. translating the inference diagrams into computer codes of LEONARDO.

3.2.1 Inference Diagrams

In the initial stage of development, inference diagrams for 21 common symptoms of faults in clarifiers serving activated sludge systems were developed as shown in Appendix A. The information for these was compiled from wastewater engineering literature [California State University and U.S. EPA, 1989; Curds and Hawkes, 1983; Water Pollution Control Federation, 1985] as well as from local domain experts in wastewater treatment. These inference diagrams underwent considerable refinement, as new information became available or comments were received.

The inference diagrams were so structured that they could easily be put into the rule-based expert system. A working prototype, CLAR_EX (version 1.0), which stands for <u>Clar</u>ifier <u>Ex</u>pert Systems, was developed using the LEONARDO Expert System Shell Version 3.20 [Creative Logic, 1989].

3.2.2 Use of LEONARDO

Initial familiarization with the LEONARDO Expert Systems Shell was done by reading the user manual and tutorial handbook, as well as reviewing the sample files. This initial work provided a good understanding of LEONARDO before deciding to use it for the development of CLAR_EX. It was found that LEONARDO provided the following benefits in system development of CLAR_EX:

a) relatively rapid prototyping can be achieved since the shell contains all the basic structures and features, such as prompt screens. This allows more time and effort to be concentrated on knowledge acquisition;
b) the Screen Designer facility of LEONARDO allows flexibility in designing user interface screens; and

c) the system allows certain flexibility in laying out the rules.

The first working prototype of CLAR_EX, was developed based on the following objectives:

a) the development of an expert system layout with simple, user-friendly and step-by-step guide to users (wastewater operators) in diagnosing clarifier operational problems, as well as providing adequate information on remedies and preventive measures for the specific problems diagnosed;
b) the development of a system that is easy to "debug" and modify; and
c) the provision of adequate help screens to guide users in obtaining information on diagnosis results, remedies and preventive measures.

3.2.3 Knowledge Representation in CLAR_EX

Basically, the layout for CLAR_EX consists of the following in the order of appearance on the screen:

a) an introduction screen to explain the purpose of CLAR_EX;
b) a series of questions to obtain information from the user, these include:
   i) nature of business which the plant serves;
   ii) type of wastewater which the plant is treating;
   iii) known pollutants in the wastewater influent;
   iv) type of clarifier (such as primary, or secondary);
   v) chemicals added to the treatment plant prior to clarification;
   vi) shape of clarifier to be diagnosed;
   vii) type of inlet;
   viii) type of outlet;
   ix) type of sludge removal; and
   x) symptom(s) identified on the clarifier;

[Note: each question above has a selection of possible answers for the user to choose]

c) a screen (or screens) on the possible cause(s) of the symptoms;
d) a series of further questions (each on a separate screen) in order to obtain details of the specific symptom(s). This helps further diagnosis and

confirmation of the likely causes. Each question requires the user to input "yes", "no", or "unknown" as a response; and

e) a screen showing a list of the most probable causes. A pop-up screen is available to each most probable cause after pressing an F4 key. The pop-up screen consists of remedies and preventive measures for a specific cause.

The rules are designed for easy debugging and modification. All the 155 rules are contained in the main rule set and sectionalized according to function. These sections include:

a) screens for possible causes;
b) checks for symptoms;
c) finding unlikely causes;
d) finding the most probable causes/remedies/preventive measures; and
e) running the consultation again.

Since Version 1.0 was developed using information obtained from the inference diagrams for the diagnosis of clarifier problems, any change in the inference diagrams would affect the knowledge base of CLAR_EX. Consequently, the "object names" used in CLAR_EX were made to resemble those of the original terms used in the inference diagrams. For example, "Nature_of_Business" in CLAR_EX can be recognized to mean the nature of business for the facility; "Poss_Cause_Small_Floc" is the object name for a screen showing possible causes for symptom of small flocs in the clarifier; and "Check_pH_Low" is the object name for asking the user a question on whether the pH of the wastewater is too low.

An example of a rule for prompting a screen for possible cause is:

if Symptom includes 'solids loss over weirs'
then use Poss_Cause_Solids_Loss.

This means that if the user selects 'solids loss over weirs' as one of the symptoms identified, then the screen Poss_Cause_Solids_Loss will appear which shows a list of possible causes for loss of solids over clarifier weirs.

To check and confirm the cause for a particular symptom, rules such as the following are set:

if Symptom includes 'floating sludge'
and Check_Sludge_Pump_Fails is Yes
then Check includes 'pump fails'

In this case, if the symptom selected includes 'floating sludge' on the clarifier, then one of the checks to be conducted is whether or not the sludge pump has failed. The "Check_Sludge_Pump_Fails" is an object name that prompts a question to ask the user whether the sludge pump fails. If the user selects 'Yes' as the response, then LEONARDO will search for a conclusive cause whose *memberslot* for check includes 'pump fails'.

CLAR_EX also contains a procedure to search for a list of the most probable causes, this is represented in the RuleSet as:

For all Cause1
if Likely_Cause includes Name: of Cause1
and Unlikely_Cause excludes Name: of Cause1
then Most_Probable_Cause includes Name: of Cause1;
scan is done

if scan is done
then run proc_unpack(number, Most_Probable_Cause);
unpack is done.

Proc_unpack is the object name of the procedure that picks all the most probable causes. The inference used in CLAR_EX to select the most probable causes is best illustrated by the Venn diagram shown in Figure 3.2. The most probable causes are listed on a screen ("screen2" as in Version 1.0) by the following rule:

if unpack is done
and number > 0
then use screen2.

Version 1.0 also allows the user to run a consultation again without executing the file from beginning, the rule used is:

if unpack is done

and restart is Yes

then cycle_mode is autocycle;

Consultation is completed.

To guide any user in answering various questions in the diagnosis, and to provide information on specific terms used in wastewater treatment, help screens were provided in Version 1.0.

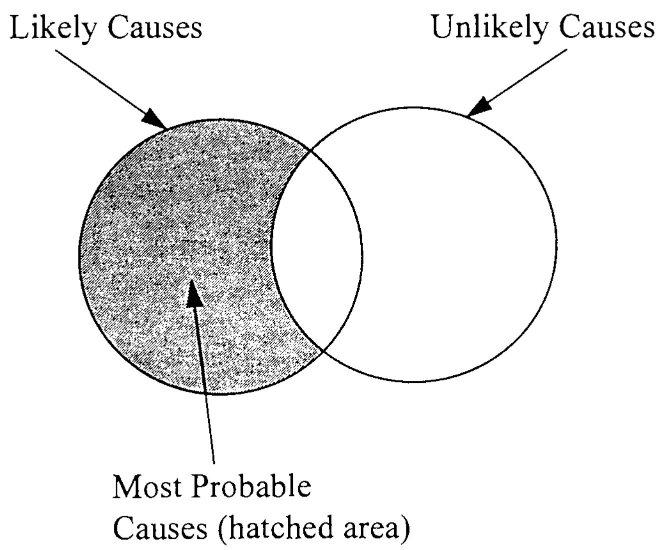

Figure 3.2 A Venn diagram illustrating the selection of the "most probable causes" in CLAR_EX

3.3 Shortcoming of CLAR_EX in Handling Uncertainties

An essential feature of an expert system that distinguishes it from a normal computer program is its ability to emulate the reasoning process of an expert. In finding the most likely causes of a problem, the expert would consider a number of factors that could cause the problem, then evaluate them mentally using his/her knowledge and past experience of the domain before coming to a final conclusion as the most likely cause.

In doing so, the expert weighs the evidence and the uncertainties associated with it and the internal relationships that govern the behaviour of the domain. The expert system must be able to handle these uncertainties in a systematic and mathematically sound way. In an attempt to incorporate this essential feature in CLAR_EX, a number of challenges were encountered.

The effective diagnosis of faults in a wastewater treatment system, or any similarly complex process, also requires bi-directional reasoning. This means that both predictive (cause to symptom) and diagnostic (symptom to cause) inferences normally have to be made within series of reasoning steps which lead to final conclusion. The exact combination and order of those predictive/diagnostic steps change dynamically, depending on the circumstances as evidence becomes available.

This requirement creates serious problems for rule-based expert systems because the rule 'if A then B (with certainty c1)' is uni-directional, and the addition of 'if B then A (with certainty C2)' will result in cyclic updating of A and B. The introduction of a diagnostic rule will necessitate the removal of a diagnostic rule, and vice versa.

This problem can be overcome with the rule-based expert system incorporating a mixture of predictive and diagnostic rules relevant to the evidence and the objective of diagnosis.

However, the reasoning mechanism remains uni-directional (forward chaining), and the use of a mixture of predictive and diagnostic rules presupposes that certain items of evidence will be presented. If this is not the case, it may lead to counterintuitive conclusion. This shows the inability of the rule-based expert system in handling bi-directional reasoning in a dynamic way. This is especially apparent when new evidence requires the retraction of existing beliefs because it 'explains away' earlier evidence which had pointed to an erroneous cause.

A simple example of a set of rules relating to faults in a clarifier given below and shown in Figure 3.3.

Rule 1: If *solids over weir*
then *short circuit* (0.4)

Rule 2: If *high hydraulic load*
then *short circuit* (0.5)

Rule 3: If *short circuit*
then *faulty baffle* (0.6)

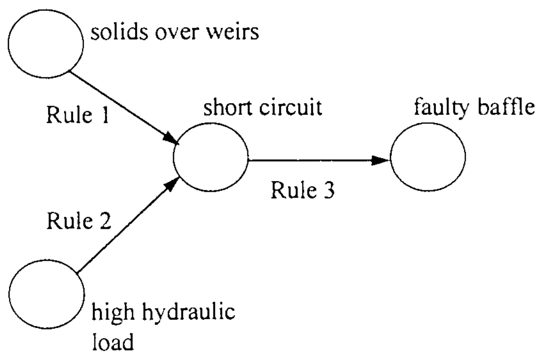

Figure 3.3 A simplified inference diagram for clarifier problems

If *solids over weir* becomes known with 90% certainty, then Rule 1 fires and gives 36% certainty for *short circuit* (i.e. 0.9 x 0.4). This will cause Rule 3 to fire, which gives *faulty baffle* with 22% certainty.

If high hydraulic load becomes known with 80% certainty, Rule 2 fires and concludes in conjunction with Rule 1 that short circuit is 62% certain (i.e. 0.30 + 0.4 - 0.36x0.4, where 0.4 is derived from 0.8x0.5 - the certainty resulting from Rule 2). This triggers Rule 3 to conclude faulty baffle with 37% certainty (i.e. 0.62 X 0.6). The new evidence (high hydraulic load) has increased the likelihood of faulty baffle (from 22% to 37%), when in actuality, this should be reduced. This is because high hydraulic load, being a cause of solids over weir, provides an alternative explanation for its occurrence.

One might argue that the above discrepancy is due to the fact that a mixture of predictive and diagnostic rules exists (Rules 1 and 3 are diagnostic, whereas Rule 2 is predictive). So, a potential solution is to change Rule 2 to its diagnostic form, that is:

Rule 2: if *short circuit* then *high hydraulic load.*

However, this makes the *high hydraulic load* worthless since it cannot fire any rule, because it occurs now as the consequent and not antecedent of the rule-base.

Alternatively, if we change Rules 1 and 3 to predictive mode, and so the three rules become:

Rule 1: if *short circuit* then *solids over weir*

Rule 2: if *high hydraulic load* then *short circuit*

Rule 3: if *faulty baffle* then *short circuit*

Then the evidence concerning the *solids over weir* becomes worthless, and it becomes impossible to conclude anything about the state of the baffle since *faulty baffle* does not appear anywhere as the consequent of a rule.

Another problem encountered involves correlated evidence. Looking at Figure 3.3 again, suppose that the evidence for solids over weir originated from two sources: a message left with your secretary by a wastewater treatment operative who is a well known joker; followed later by a telephone call from the plant manager. Your initial doubts about the validity of the message were overcome when you receive the plant manager's call, but then were later renewed when you discover later the plant manager had gained his information from the same operative. These two sources of evidence, which were initially thought to be independent, were found to be correlated and your conclusion was modified accordingly. This type of situation creates enormous difficulties in rule-based systems, because of their assumption of detachment (that is, their rules apply regardless of how the antecedent was derived) [Krause and Clark, 1993]. Heckerman [1990] mentioned that systems which update certainty factors in a modular and consistent way only produce coherent updates if no two rules stem from the same premise.

In addition, the possible states of the antecedents and consequences of the rules have so far been assumed binary (such as yes or no, present or absent, high or low), but in fact, they may have several possible states. For example, hydraulic load could have three states: low, normal and high. Under such a situation, it will be necessary to have a rule for each possible combination of the antecedent and consequent states. This means a single relationship between an antecedent with three possible states and an consequent with four possible states would require twelve separate rules. For most diagnostic systems, such as the one developed for this project, this would involve a very large number of rules to cover all the possible combinations of each antecedent and consequent. This would certainly undermine the computational efficiency of the rule-based approach. However, this is a relatively minor weakness compared to its weaknesses with respect to bi-directional reasoning and correlated evidence.

In understanding the weaknesses of CLAR_EX in handling uncertainties, it was decided to move on the research work by using Bayesian Belief Network which has shown potentials in handling plausible reasoning. However, there were a number of positive contributions in CLAR_EX which are essential to the subsequent research work in developing CLAR_NET using the Bayesian Belief Network. The inference diagrams developed provided a good foundation for constructing the causal structure of CLAR_NET. In addition, the knowledge elicited from the experts for CLAR_EX have also saved tremendous time and efforts in the developing CLAR_NET. The development of CLAR_NET is described in more detail in the next chapter.

CHAPTER 4 THEORY AND APPLICATION OF BAYESIAN BELIEF NETWORKS

4.1 Introduction

This chapter covers the theory of Bayesian Belief Networks and demonstrates its application to the diagnosis of faults in wastewater treatment plant. It applies a simple example based on a subset of nodes from the full network developed during the project. It also presents the work published by Chong and Walley (1996) in greater detail than was possible in the published paper. For example, the maximum cardinality search and the propagation of probabilities in Bayesian Belief Networks is presented here in full.

4.2 Background of Bayesian Belief Networks

In considering how the human mind reasons, Pearl [1988] initiated a method of propagating probabilities in Bayesian Belief Networks (BBNs). These networks, which are sometimes referred as Causal Networks or Belief Networks, are based on the essential concepts from probability theory.

It is believed that BBNs are to a large segment of the Artificial Intelligence community (that is, those involved in reasoning under uncertainty) what resolution theorem proving is to the AI-logic community [Charniak, 1991]. Despite its potential, the early development and application of this approach in the expert systems field were hampered by the complexity of its theory. Researchers were attracted to the rule-based approach to expert systems due to its convenience in computation.

This chapter will describe the essential concepts in Bayesian Belief Networks, and an example will be made which illustrates the use of such a system. The example is based on a simplified version of the BBN which has been developed to diagnose faults in the activated sludge system of the wastewater treatment process.

4.3 Characteristics of BBNs

Some of the concepts behind BBNs have been discussed in Chapter 2, and will not be repeated here. Basically, BBNs are directed acyclic graphs (DAGs), where the nodes are variables, and certain independence assumptions hold. Often, the variables can be thought of as states of affairs, and the variables have a set of possible values.

BBNs allow updating of the beliefs in a hypothesis in response to the observation of evidence. The heart of Bayesian techniques lies in the inversion formula,

$$P(B|A) = \frac{P(A|B)P(B)}{P(A)} \tag{4.1}$$

Where, P(B| A) is the revised belief in hypothesis B on observing evidence A, P(A) and P(B) are the prior beliefs in A and B, and P(A| B)is the probability of A given B. It should be noted that Equation 4.1 allows the reverse in direction of reasoning from P(B| A) to P(A| B).

In the probabilistic approach, the conditional probability $P(B|A_1)=p_1$ means that if A_1 is observed, and A_1 is the only thing that is known which is relevant to the outcome B, then probability p_1 can be attached to the outcome B. If additional evidence, such as (A1,A2,...An) is observed, then a new conclusion will be made with $p(B)=p_2$ to replace the previous conclusion of $p(B)=p_1$, where p_2 is the known or derived value of the conditional probability p(B |A1,A2,A3,..An). An item of evidence can only be ignored during the evaluation of p(B) if it is irrelevant to the outcome B. This is also true for the rule-based system. However, Pearl [1988] pointed out that " the computational convenience of these systems and their striking resemblance to logical derivation tempt people to neglect the importance of verifying irrelevance".

The computational challenges in the probabilistic approach was overcome by recent research in this area [Lauritzen and Spiegelhalter, 1988; Pearl, 1988 and Neapolitan, 1990]. This prompted the development of a computational method based on graphical representation of dependencies and efficient updating algorithms based on the dependency structure. This method involves extraction of an *undirected triangulated graph* from the *directed acyclic graph* (DAG) in the Bayesian Belief Network, and the creation of a tree whose vertices are the cliques of this triangulated graph. Such a tree is called a "join tree" or "hypertree" of cliques. Once this tree is built, it is no longer referred to as a DAG. In order to update the probabilities in the original causal network, messages are spread through the vertices in this tree. The extent to which the message is transmitted through the network depends on whether the node receiving hard evidence is *d-connected* to or d-*separated* from other nodes in the network. If nodes are *d-connected*, this means messages can be transmitted between these nodes. (Section 4.6 contains detail explanations on *d-connection* and *d-separation*). This method is sometimes called "probability propagation in trees of cliques" [Lauritzen and Spiegelhalter, 1988], or "belief propagation through local computation" as explained in detail by Krause and Clark [1993].

The method is best illustrated by the following simple example, which has been extracted from the full network (refer to Figure 5.5) for diagnosing faults in the activated sludge plant of a wastewater treatment system.

4.4 An Example Illustrating the Use of BBN

Figure 4.1 shows a simple Bayesian network of a small part of a wastewater treatment plant. For the purpose of easy illustration, most of the nodes and links from the original network (Figure 5.5) have been omitted. It should be noted that certain aspects of the behaviour of the network might be considered odd by an experienced plant operator. This is purely the result of over-simplification for the sake of clarifying the BBN concepts.

In graphical terms, the network is known as a directed acyclic graph (DAG). That is, a graph with arcs (directed links) from *parent* nodes (causes) to *child* nodes (effects) which do not form a closed cycle anywhere in the structure. By looking at the dependency structure of the network, its joint probability distribution can be expressed as the product of the nodes' conditional probabilities (conditioned on their parents):

$$P(A,B,..H) = P(H|D,E)P(G|E)P(F|D)P(E|B,C)P(D|A)P(C|A)P(B)P(A) \tag{4.2}$$

The DAG is then transformed to an undirected triangulated graph as shown in Figure 4.2. The triangulation process is done in two stages:

a) provide links between unjoined *parents* of a common *child* as shown by the dotted lines as shown in Figure 4.2, and

b) complete the triangulation by introducing additional links to ensure that there are no remaining cycles of lengths four or more without a chord.

The triangulated graph is then decomposed into a sequence of subsets of nodes, known as "cliques", within which each node is linked to every other node. Figure 4.3 shows the six cliques which are formed by decomposing Figure 4.2. The structure has the important property that its joint probability distribution is equal to the product of the joint distributions on the cliques divided by the product of the joint distributions on the intersections. That is,

$$P(A,B,..H) = \frac{P(A,C,D)P(C,D,E)P(B,C,E)P(D,E,H)P(D,F)P(E,G)}{P(C,D)P(E,C)P(E,D)P(D)P(E)} \tag{4.3}$$

Equation (4.3) is the same as Equation (4.2), except it is expressed in a more useful form (A proof of this equivalence derived by Walley (1996) is reproduced in the appendix). The power of this formulation lies in its ability to enable belief revision to be calculated locally within cliques and then propagated sequentially from clique to clique. This forms the essential key to computational efficiency of the new updating algorithms for this approach.

The cliques making up the decomposed structure in Figure 4.3 were then labelled as cliques C1 to C6 using a standard procedure known as *maximum cardinality search*. Figure 4.4 shows the hypertree of cliques to which the decomposed structure is transformed. This method, initiated by Tarjan and Yannakakis [1984], is defined by Neapolitan [1990] as "an ordering of the vertices by assigning 1 to an arbitrary vertex. For the next vertex to number, the vertex adjacent to the largest number of previously numbered vertices is selected, breaking ties arbitrarily". In Figure 4.3, the first label C1 is given to the clique containing the node H, simply because evidence will be introduced to the network via this node in the example given here. The labelling is then continued by successively numbering the nodes attached to the maximum

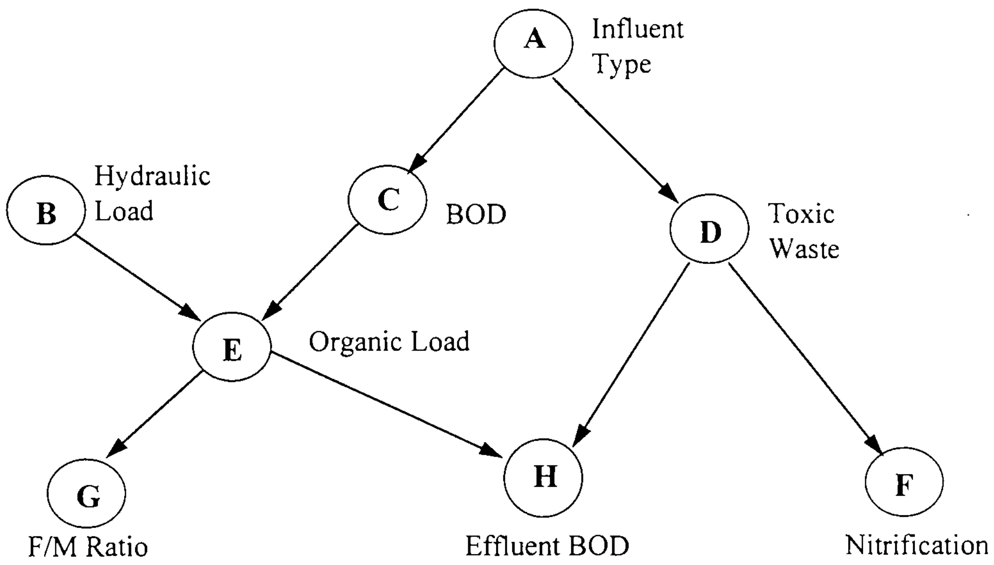

Figure 4.1 The example network

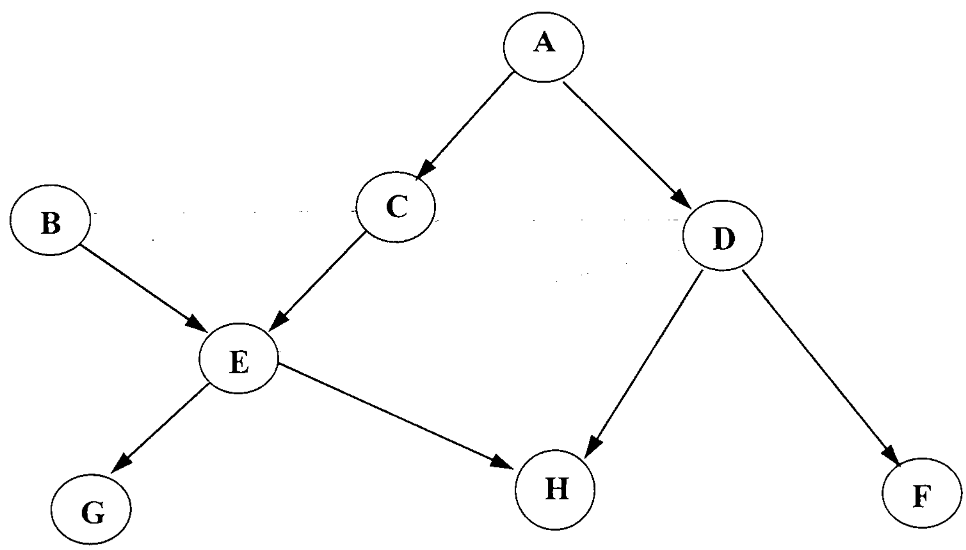

Figure 4.2 The triangulated graph

number of nodes that are already labelled, and ties may be broken at random. Cliques C2 to C6 are thus labelled as shown in Figure 4.3.

The six cliques are then re-arranged to form a directed *hypertree* (Figure 4.4), which is a tree of cliques as opposed to a network of nodes. This is a directed graph, with arrows showing the direction in which the updating of the belief is propagated from a clique to another when new evidence in C1 is received. As each clique receives an update of belief through the intersection with the previous clique, its own nodes are updated prior to transmitting the new belief on to another clique via the intersections.

This means the updating of beliefs in all the nodes in the Bayesian Belief Network due to the evidence input is done in a systematic and consistent approach, and in line with sound mathematical method. The approach will be valid for diagnostic (consequences to causes) or predictive (causes to consequences) reasoning, or a combination of both. The graphical representation of the dependencies between variables explicitly covers matters of relevance and irrelevance, and problems of correlated evidence do not arise because they are explicit in the network and properly represented mathematically. As such, BBNs do not suffer from any of the problems which bedevil rule-based methods of plausible reasoning.

4.4.1 Procedure for Analysis of Probabilities in BBN

The structure for the above example BBN as shown in Figure 4.1 has associated with it a set of assigned prior and conditional probabilities. Together, the probabilities and the structure of the BBN effectively form the *knowledge base* of the system. Table 4.1 shows the probabilities of all possible states of each node given the state of its parents, that is, *the conditional probability* for each node. For nodes such as A and B which have no parents, they are assigned *prior probabilities* for each possible state. All these *prior* and *conditional probabilities* are obtained initially from the author's knowledge and experience in wastewater treatment operations, with subsequent refinements made from comments by the two domain experts, P. Nungesser and H.A. Hawkes. These probabilities are subjective in nature in that they represent only the best estimates from the author and the two domain experts.

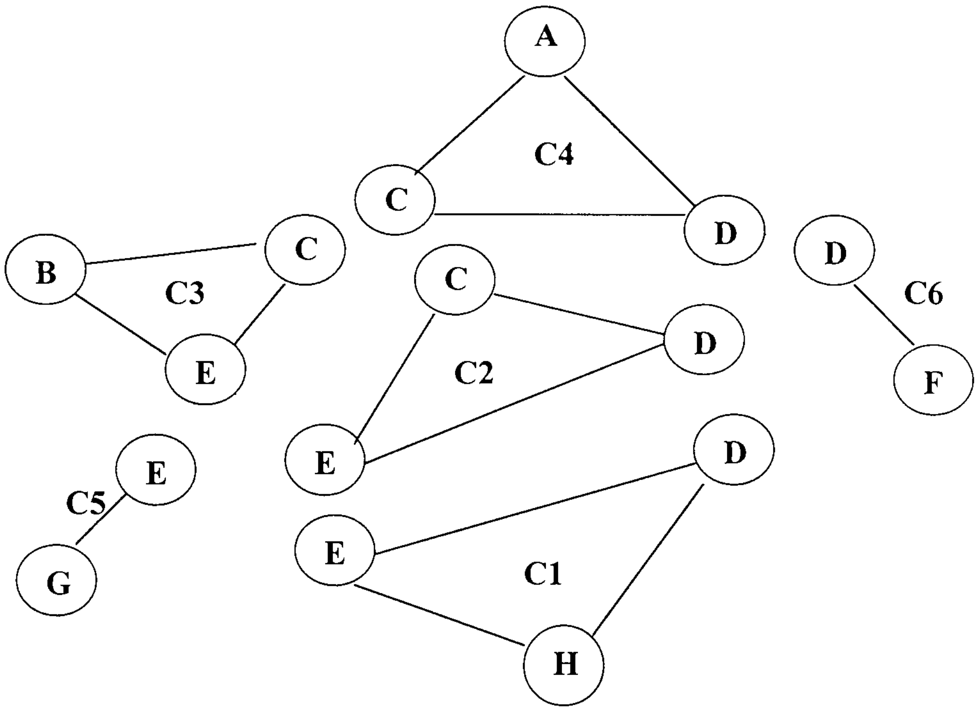

Figure 4.3 The arrangement of the cliques

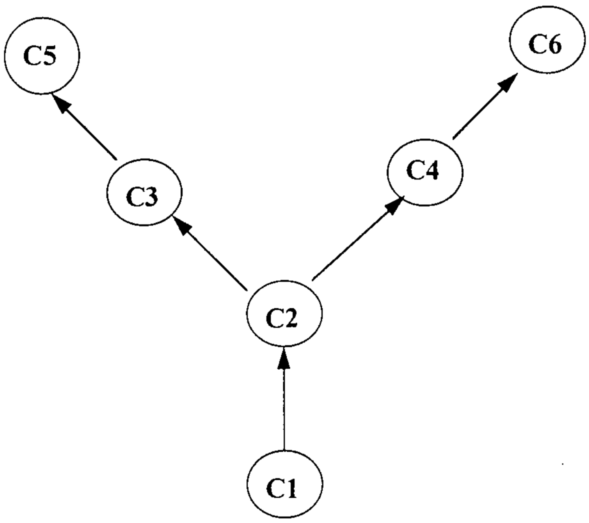

Figure 4.4 Hypertree of cliques

Table 4.1 Prior and conditional probabilities in the example network

Influent Type (A) High		**Hydraulic Load (B)**		**F/M Ratio (G)**	Organic Load		
					Low	Normal	
Industrial	0.55	Low	0.025	Low	0.60	0.01	0.01
Domestic	0.20	Normal	0.950	Normal	0.39	0.98	0.39
Mixed	0.25	High	0.025	High	0.01	0.01	0.60

Influent BOD (C)	Influent Type (A)			**Toxic Waste**	Influent Type (A)			**Nitrific-ation (F)**	ToxicWaste(D)	
	Ind.	Dom.	Mix		Ind.	Dom.	Mix		Yes	No
Normal/low	0.95	0.90	0.92	Yes	0.10	0.05	0.08	Normal	0.20	0.95
High	0.05	0.10	0.08	No	0.90	0.95	0.92	Abnormal	0.80	0.05

Organic Load (E)	Influent BOD (C)					
	Normal/Low			High		
	Hydraulic Load (B)			Hydraulic Load (B)		
	Low	Normal	High	Low	Normal	High
Low	0.90	0.25	0.02	0.05	0.02	0.01
Normal	0.08	0.70	0.45	0.90	0.38	0.05
High	0.02	0.05	0.53	0.05	0.60	0.94

Effluent BOD (H)	Toxic Waste (D)					
	Yes			No		
	Organic Load (E)			Organic Load (E)		
	Low	Normal	High	Low	Normal	High
Lw/Normal	0.60	0.50	0.05	0.98	0.95	0.65
High	0.40	0.50	0.95	0.02	0.05	0.35

The procedure for performing data processing in a BBN proceeds as follows.

a. Calculate the joint probabilities on the cliques which have nodes with known prior probabilities. For example in Clique 4 where P(A) is known:

$$P(A,C,D) = P(C/A)\ P(D/A)P(A) \qquad (4.4)$$

and so,

$$P(A1,C1,D1) = P(C1/A1)\ P(D1/A1)P(A1) \qquad (4.5)$$

where, A1 represents "industrial influent type", C1 represents "normal/low influent BOD", and D1 for "presence of toxic waste", and from Table 4.1,

P(A1) = 0.55, P(C1 | A1) = 0.95, and P(D1 | A1)= 0.10,

and substituting into Eqn.(4.5) becomes:

P(A1,C1,D1) = 0.95 x 0.10 x 0.55 = 0.05225

The same procedure follows to calculate the other joint probabilities and results of the computation is shown in Table 4.2

b. Derive the joint probabilities, P(C,D) on intersection CD and the prior probabilities, P(C) and P(D), on nodes C and D respectively.

Following the above example on the first state of conditions and referring to Table 4.2:

$$P(C1,D1) = P(A1,C1,D1)+ P(A2,C1,D1)+ P(A3,C1,D1)$$

$$= 0.05225 + 0.009 + 0.0184$$

$$= 0.07965$$

c. Progress through the whole network until the joint probabilities on all the cliques and intersections plus the prior probabilities on the nodes have been evaluated. The latter correspond to the BBN's belief in the initial state of the system prior to any evidence given.

From Table 4.2,

$$P(C1) = P(A1,C1,D1) + P(A1,C1,D2) + P(A2,C1,D1)$$

$$+ P(A2,C1,D2) +P(A3,C1,D1) + P(A3,C1,D2)$$

$$= 0.05225 + 0.47025 + 0.009 + 0.171 + 0.0184 + 0.2116$$

$$= 0.9325$$

Case X in Table 4.3 illustrates the states of condition where there is no evidence.

Table 4.2 Results of computation for the nodes probabilities of the example network

C1(D,E,H)									Intersection (DE)		
	P(D,E,H)	Let P(H2)=1		P'(DE)		P'(D)	P(D)	P'(D)/P(D)		P(DE)	P'(DE)/P(DE)
D1,E1,H2	0.004172	P(H2)=	D1,E1	0.040913	D1	0.33601	0.085	3.953059	D1,E1	0.020859	1.961440
D1,E2,H2	0.022432	0.101966	D1,E2	0.219999	D2	0.66399	0.915	0.725672	D1,E2	0.056081	3.922880
D1,E3,H2	0.007657		D1,E3	0.075098					D1,E3	0.008060	9.316841
D2,E1,H2	0.011172		D2,E1	0.109567		P'(E)	P(E)	P'(E)/P(E)	D2,E1	0.223442	0.490360
D2,E2,H2	0.003012		D2,E2	0.029537	E1	0.150479	0.2443	0.615962	D2,E2	0.602358	0.049036
D2,E3,H2	0.053520		D2,E3	0.524886	E2	0.249536	0.658439	0.378982	D2,E3	0.089201	5.884321
D2,E2,H1	0.597226				E3	0.599984	0.097261	6.168789			
D1,E2,H1	0.033169										
D2,E3,H1	0.045217										
D1,E1,H1	0.009270										
D2,E1,H2	0.078766										
D1,E3,H2	0.134387										

C2(C,D,E)											
	P(C,D,E)	P'(C,D,E)		P(CE)	P'(CE)		P(CD)	P'(CD)	P'(CD)/P(CD)		P'(C)
C1,D1,E1	0.020749	0.040698	C1,E1	0.242916	0.149640	C1,D1	0.07965	0.298075	3.742305	C1	0.742761
C1,D1,E2	0.054023	0.211924	C1,E2	0.632468	0.240289	C1,D2	0.85285	0.444686	0.521412	C2	0.257239
C1,D1,E3	0.004879	0.045443	C1,E3	0.057116	0.352832	C2,D1	0.00535	0.037935	7.090729		
C1,D2,E1	0.222167	0.108942	C2,E1	0.001384	0.000840	C2,D2	0.06215	0.219304	3.528619		
C1,D2,E2	0.578446	0.028365	C2.E2	0.025971	0.009247					C1	0.9325
C1,D2,E3	0.052237	0.307380	C2,E3	0.040146	0.247150					C2	0.0675
C2,D1,E1	0.000110	0.000215									
C2,D1,E2	0.002058	0.008075									
C2,D1,E3	0.003182	0.029645									
C2,D2,E1	0.001274	0.000625									
C2,D2,E2	0.023912	0.001173									
C2,D2,E3	0.036964	0.217506									

Table 4.2 Results of computation for the node probabilities of the example network (Continued)

C3(B,C,E)

	P(B,C,E)	P'(B,C,E)		P'(CE)/P(CE)		P(B)
B1,C1,E1	0.020981	0.012925	C1,E1	0.616013	B1	0.025
B1,C1,E2	0.001865	0.000709	C1,E2	0.379923	B2	0.950
B1,C1,E3	0.000466	0.002880	C1,E3	6.177511	B3	0.025
B1,C2,E1	0.000084	0.000051	C2,E1	0.606957		
B1,C2,E2	0.001519	0.000541	C2,E2	0.356074		P'(B)
B1,C2,E3	0.000084	0.000519	C2,E3	6.156380	B1	0.017625
B2,C1,E1	0.221469	0.136428			B2	0.891969
B2,C1,E2	0.620113	0.235595			B3	0.090406
B2,C1,E3	0.044294	0.273625				
B2,C2,E1	0.001283	0.000778				P(A)
B2,C2,E2	0.024368	0.008677			A1	0.55
B2,C2,E3	0.038475	0.236867			A2	0.20
B3,C1,E1	0.000466	0.000287			A3	0.25
B3,C1,E2	0.010491	0.003986				
B3,C1,E3	0.012356	0.076327				P'(A)
B3,C2,E1	0.000017	0.000010			A1	0.547562
B3,C2,E2	0.000084	0.000030			A2	0.196977
B3,C2,E3	0.001586	0.009766			A3	0.255461

C4(A,C,D)

	P(A,C,D)	P'(A,C,D)		P'(C,D)/P(C,D)
A1,C1,D1	0.05225	0.195535	C1,D1	3.742305
A1,C1,D2	0.47025	0.245194	C1,D2	0.521412
A1,C2,D1	0.00275	0.019500	C2,D1	7.090729
A1,C2,D2	0.02475	0.087333	C2,D2	3.528619
A2,C1,D1	0.00900	0.033681		
A2,C1,D2	0.17100	0.089161		
A2,C2,D1	0.00100	0.007091		
A2,C2,D2	0.01900	0.067044		
A3,C1,D1	0.01840	0.068858		
A3,C1,D2	0.21160	0.110331		
A3,C2,D1	0.00160	0.011345		
A3,C2,D2	0.01840	0.064927		

C5(E,G)

	P(E,G)	P'(E,G)		P'(E)/P(E)		P(G)
E1,G1	0.146580	0.090288	E1	0.615962	G1	0.154137
E2,G1	0.006584	0.002495	E2	0.378982	G2	0.778479
E3,G1	0.000973	0.006000	E3	6.168789	G3	0.067384
E1,G2	0.095277	0.058687				
E2,G2	0.645270	0.244546				P'(G)
E3,G2	0.037932	0.233994			G1	0.098783
E1,G3	0.002443	0.001505			G2	0.537226
E2,G3	0.006584	0.002495			G3	0.363991
E3,G3	0.058357	0.359999				

C6(D,F)

	P(D,F)	P'(D,F)		P(F)
D1,F1	0.01700	0.067202	F1	0.92285
D2,F1	0.90585	0.657350	F2	0.07715
D2,F1	0.06800	0.268808		
D2,F2	0.00915	0.006640		
				P'(F)
	P'(D)/P(D)		F1	0.724552
D1	3.953059		F2	0.275448
D2	0.725672			

d. When an evidence is given, say, effluent BOD (node H) is high, which means P(H2)=1 and P(H1)=0. The effect of such is propagated through the hypertree of cliques in Figure 4.4. This involves the following process:

i) derive the revised joint probabilities on intersection DE, P'(D,E) as:

$$P'(D,E) = P(D,E/H2) \tag{4.6}$$

for example, $P'(D1,E1) = P(D1,E1,H2)/P(H2)$

Since $P(H2) = P(D1,E1,H2) + P(D1,E2,H2) + P(D1,E3,H2) + P(D2,E1,H2) + P(D2,E2,H2) + P(D2,E3,H2)$

= 0.101966 (see Table 4.2)

P'(D1,E1) = 0.004172/0.101966 = 0.040913

ii) derive the revised joint probabilities P'(C,D,E) on clique C2 by multiplying its original joint probability P(C,D,E) by the ratio of the revised to the original joint probabilities on the intersection with clique C1; that is,

$$P'(C,D,E)=P(C,D,E)P'(D,E)/P(D,E) \tag{4.7}$$

following from the above example (Table 4.2),

$P'(C1,D1,E1) = P(C1,D1,E1).P'(D1,E1)/P(D1,E1)$

= 0.020749 x 0.040913 / 0.020859

= 0.040698

iii) the joint probabilities on the remaining intersections and cliques are revised the same way. In each case the joint probabilities on the cliques are revised by multiplying them by the ratio of the revised to the original joint probabilities on the intersection with the previous clique;

iv) the updating is completed by deriving the revised probabilities on the nodes from the revised joint probabilities on the cliques or intersections. This gives the network's belief in the state of the system following the introduction of the evidence that effluent BOD is high. This is represented by Case Y in Table 4.2; and

v) if additional evidence is introduced, for example if Nitrification is abnormal (that is, at node F, set P'(F2)=1.0), then the effect of this is propagated through a new hypertree of the six cliques, starting from node F. Thus, the order of propagation from C1 to C6 becomes C4, C3, C5, C2, C6 and C1 respectively. The final belief in the state of the system following the introduction of this second piece of evidence is represented by Case Z in Table 4.3.

The results from two pieces of evidence can be summarised below.

a. Prior to the introduction of evidence to the contrary, the network indicated very high probabilities that each component was functioning normally.

b. When evidence was introduced to the network (as in Case Y where effluent BOD is high), the network significantly increased its belief in the abnormal functioning of some components. The most notable changes were increased expectations of:

   i) high organic load (from 0.097 to 0.354),
   ii) high F/M ratio (0.067 to 0.219),
   iii) increase in presence of toxic waste (0.085 to 0.401),
   iv) abnormal nitrification (0.114 to 0.351), and
   v) high influent BOD (0.068 to 0.166).

   From the above results, the most likely cause of high effluent BOD is the presence of toxic waste, which in turn should cause abnormal nitrification. However, it also suggests that high organic load could equally be the cause of the problem. It can be seen that responses (i), (iii) and (v) follow from diagnostic reasoning from the evidence presented, but responses (ii) and (v) required predictive reasoning from responses (i) and (iii) respectively.

c. When the second piece of evidence is introduced (as in Case Z where Nitrification is abnormal, in addition to the high effluent BOD), the network strengthens its belief that the waste is toxic (i.e. from 0.401 to 0.915) and retracts its beliefs in the other possible causes, such as high organic load (down from 0.354 to 0.200), high F/M ratio (0.219 to 0.129) and high influent BOD (0.166 to 0.103).

Results obtained after evaluating the two pieces of evidence, show that the most likely cause of the problem is the presence of toxic waste. In reaching such conclusion, the network has used both diagnostic and predictive reasoning to retract its earlier beliefs in other causes, since these have been *explained away* by the new evidence.

Table 4.3 Beliefs in the state of the example network resulting from three consultations

NODE	STATE	X	Y	Z
A - Influent Type	a1. Industrial	0.550	0.568	0.632
	a2. Domestic	0.200	0.182	0.129
	a3. Mixed	0.250	0.250	0.239
B - Hyraulic Load	b1. Low	0.025	0.015	0.020
	b2. Normal	0.950	0.925	0.941
	b3. High	0.025	0.060	0.039
C - Influent BOD	c1. Low/Normal	0.933	0.834	0.897
	c2. High	0.068	0.166	0.103
D - Toxic Waste	d1. Yes	0.085	0.401	0.915
	d2. No	0.915	0.599	0.085
E - Organic Load	e1. Low	0.244	0.117	0.179
	e2. Normal	0.658	0.529	0.621
	e3. High	0.097	0.354	0.200
F - Nitrification	f1. Normal	0.886	0.649	0
	f2. Abnormal	0.114	0.351	1
G - F/M Ratio	g1. Low	0.154	0.079	0.116
	g2. Normal	0.779	0.702	0.756
	g3. High	0.067	0.219	0.128
H - Effluent BOD	h1. Low/Normal	0.890	0	0
	h2. High	0.110	1	1

Case X: Prior State (no evidence at all) Case Y: Evidence that Effluent BOD is high
Case Z: Evidence that Effluent BOD is high and Nitrification is abnormal

This simple example has clearly illustrated two important features of Bayesian Belief Networks: it emulates human reasoning using integrated diagnostic-predictive reasoning, and retracts belief when potential causes are explained away by new evidence.

4.5 Comparison between the Example Network and CLAR_NET

Since the example network is only a small subset of the full CLAR_NET structure (Figure 4.5), it may be immune to the effect of some neighbouring nodes which might otherwise influence its conclusion. To demonstrate the effect of this immunity, CLAR_NET was subjected to the same three consultations (Cases X, Y and Z). The results for the eight nodes which were common to the Example Network, are presented in Table 4.4

The main differences between the two sets of results (Tables 4.3 and 4.4) for Case Z (Evidence that Effluent BOD is high and Nitrification is Abnormal) are that the likelihood of the toxic waste being the cause of the problems is reduced from 0.915 (in Table 4.3) to 0.826 (Table 4.4), whilst the likelihood of the high organic load being the cause is increased from 0.200 to 0.536. As such, the full network (CLAR_NET) is far less certain that toxic waste is the cause of the problem and considers it could also be due to high organic load, possibly resulting from high hydraulic load (up from 0.039 to 0.425), and/or due to high influent BOD (up from 0.103 to 0.322). As one might expect, results from the full network are more in line with the opinion of human experts than those given in the Example Network.

The reason for the differences is that in the full network (CLAR_NET), there are additional nodes which interconnect with and exert influence on the eight nodes used in the Example Network. In fact, the most influential extra link was one between two of the eight nodes in the Example Network (that is, the F/M Ratio (FMRatio) node is a parent of Nitrify node in CLAR_NET). This link was not included in the Example Network because it would have made the mathematics and explanation unnecessarily complex. The development of CLAR_NET is described in detail in the next chapter.

Table 4.4 Beliefs in the state of the eight nodes of the example network within CLAR_NET

NODE	STATE	X	Y	Z
A - Influent Type	a1. Industrial	0.550	0.571	0.666
	a2. Domestic	0.200	0.200	0.155
	a3. Mixed	0.250	0.229	0.179
B - Hyraulic Load	b1. Low	0.030	0.019	0.023
	b2. Normal	0.910	0.723	0.552
	b3. High	0.060	0.258	0.425
C - Influent BOD	c1. Low/Normal	0.949	0.804	0.678
	c2. High	0.051	0.196	0.322
D - Toxic Waste	d1. Yes	0.055	0.327	0.826
	d2. No	0.945	0.673	0.174
E - Organic Load	e1. Low	0.245	0.099	0.103
	e2. Normal	0.651	0.435	0.361
	e3. High	0.104	0.467	0.536
F - Nitrification	f1. Normal	0.912	0.764	0
	f2. Abnormal	0.088	0.236	1
G - F/M Ratio	g1. Low	0.149	0.064	0.065
	g2. Normal	0.786	0.654	0.564
	g3. High	0.065	0.282	0.371
H - Effluent BOD	h1. Low/Normal	0.902	0	0
	h2. High	0.098	1	1

Case X: Prior State (no evidence at all) Case Y: Evidence that Effluent BOD is high
Case Z: Evidence that Effluent BOD is high and Nitrification is abnormal

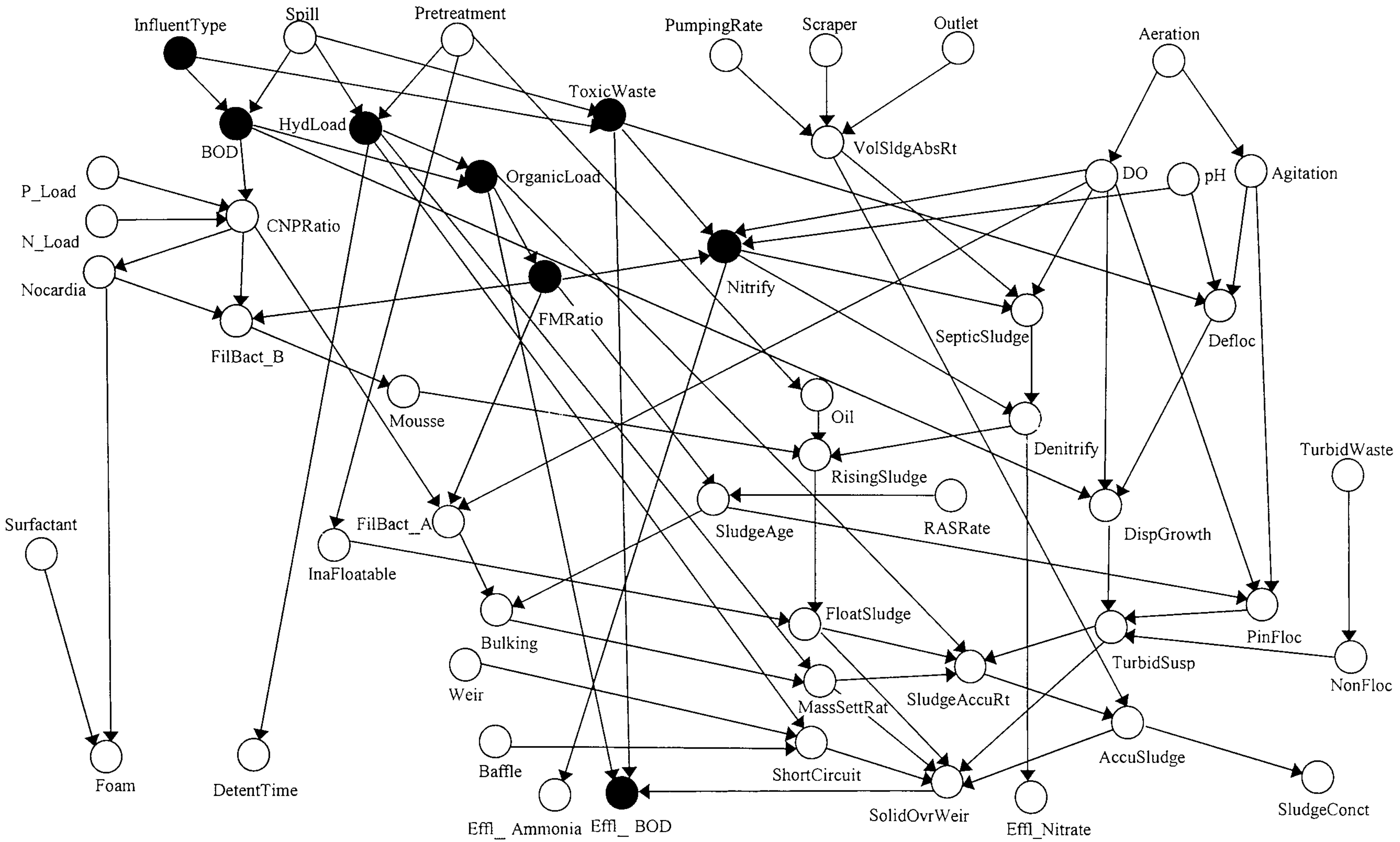

Figure 4.5 The full structure of CLAR_NET with shaded nodes indicating those in the Example Network

4.6 Transmtting Messages through *d-connected* Nodes

Pearl (1988) defined the notion of *d-separation* in causal networks. Jensen [1996] stated that "two variables A and B in a causal network are *d-separated* if, for all paths between A and B, there is an intermediate variable C such that either the connection is serial (that is chain-connected) or diverging and the state of C is known, or the connection is converging and neither C nor any of C's descendants have received evidence". This simply means that, if A and B are *d-separated*, the message cannot pass from A to B, or from B to A. However, if A and B are *d-connected*, the message can pass from A to B, and vice versa. Thus, if A and B are not *d-connected*, they are then *d-separated.*

The relationship of nodes A and B can be illustrated in the following three types of node structure as illustrated below.

<u>a) Chained Nodes</u> - Node A has an influence on C which has an influence on B as shown in Figure 4.6. Evidence about A will affect the likelihood of C and subsequently the certainty of B. However, if there is *hard* evidence at C, then A and B are *d-separated* and become independent (Figure 4.7). *Hard* evidence means an exact state of the variable is known, that is, a 100% certainty.

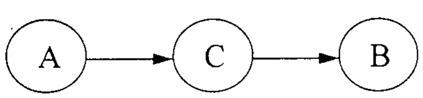

Figure 4.6 A and B are *d-connected* and dependent

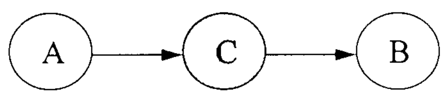

Fig. 4.7 With hard evidence at C, A and B are d-separated and independent

<u>b) Converging Nodes</u> - In Figure 4.8, if nothing is known about C, then parent nodes A and B are independent and d-separated. This means that evidence on A has no influence on the likelihood of B and vice versa. However, if hard evidence is known at C, then A and B will be *d-connected* and hence dependent (Figure 4.9). In a more complex structure as shown in Figure 4.10, soft evidence at C due to hard evidence at E is sufficient to make A and B dependent and hence d-connected.

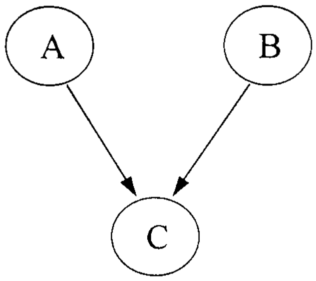

Figure 4.8 A and B are independent and d-separated

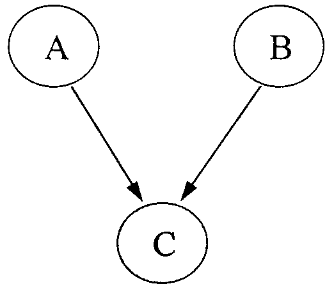

Figure 4.9 With hard evidence at C, A and B are d-connected and dependent.

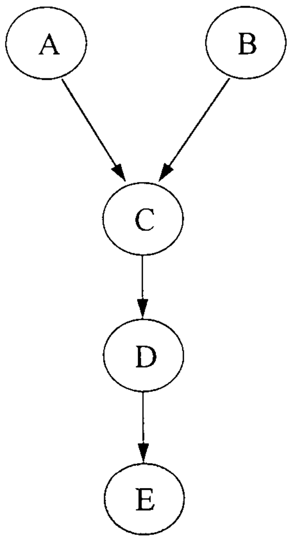

Fig. 4.10 A and B are d-connected with soft evidence at C due to hard evidence at E

c) Diverging Nodes - In this case, A and B are children of C and are d-connected and dependent if there is no hard evidence at C (Figure 4.11). However, hard evidence at C will block the message between A and B, and so A and B are independent and d-separated given C (Figure 4.12).

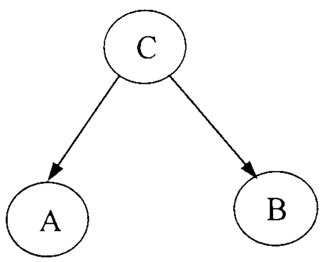

Figure 4.11 A and B are d-connected and dependent

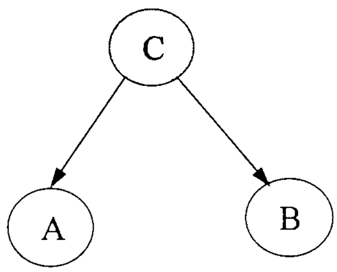

Figure 4.12 A and B are d-separated and independent with hard evidence at C

The *d-connection* concept will be applied more extensively in the sensitivity tests for CLAR_NET in Chapter 6.

CHAPTER 5 DEVELOPMENT OF BAYESIAN BELIEF NETWORK CLAR_NET

5.1 Development Process

In Chapter 3, the process and challenges involved in developing the initial diagnostic model for the clarifier system were described in detail. The inadequacy of the rule-based expert system model, CLAR_EX, to handle uncertainty together with its other limitations, such as its inability to properly update beliefs resulting from correlated evidence, led to the adoption of an alternative system.

The Bayesian Belief Network (BBN) system was chosen, since it possesses superior capabilities over the rule-based expert system and is free of the weaknesses mentioned above. The theory and algorithm involved in the BBN approach were described in Chapter 4.

In this chapter, the process involved in constructing the Bayesian Belief Network, is described in detail. There are a number of processes involved (as shown in Figure 5.1), but the three main steps are : constructing the structure of the belief network; eliciting and inputing the probabilities into the network; and testing CLAR_NET to check its validity. The first two processes will be described in this chapter, whereas testing of CLAR_NET is covered in Chapter 6.

The Bayesian Belief Network (BBN) which was developed to replace CLAR_EX was named CLAR_NET (clarifier belief network). Figure 5.2 shows the extent to which CLAR_NET covers a typical wastewater treatment operation. The development work for CLAR_NET was carried out on an Apple Macintosh computer using ERGO, a Bayesian Belief Network package from Noetic Systems (E-mail: noetic@applelink.apple.com).

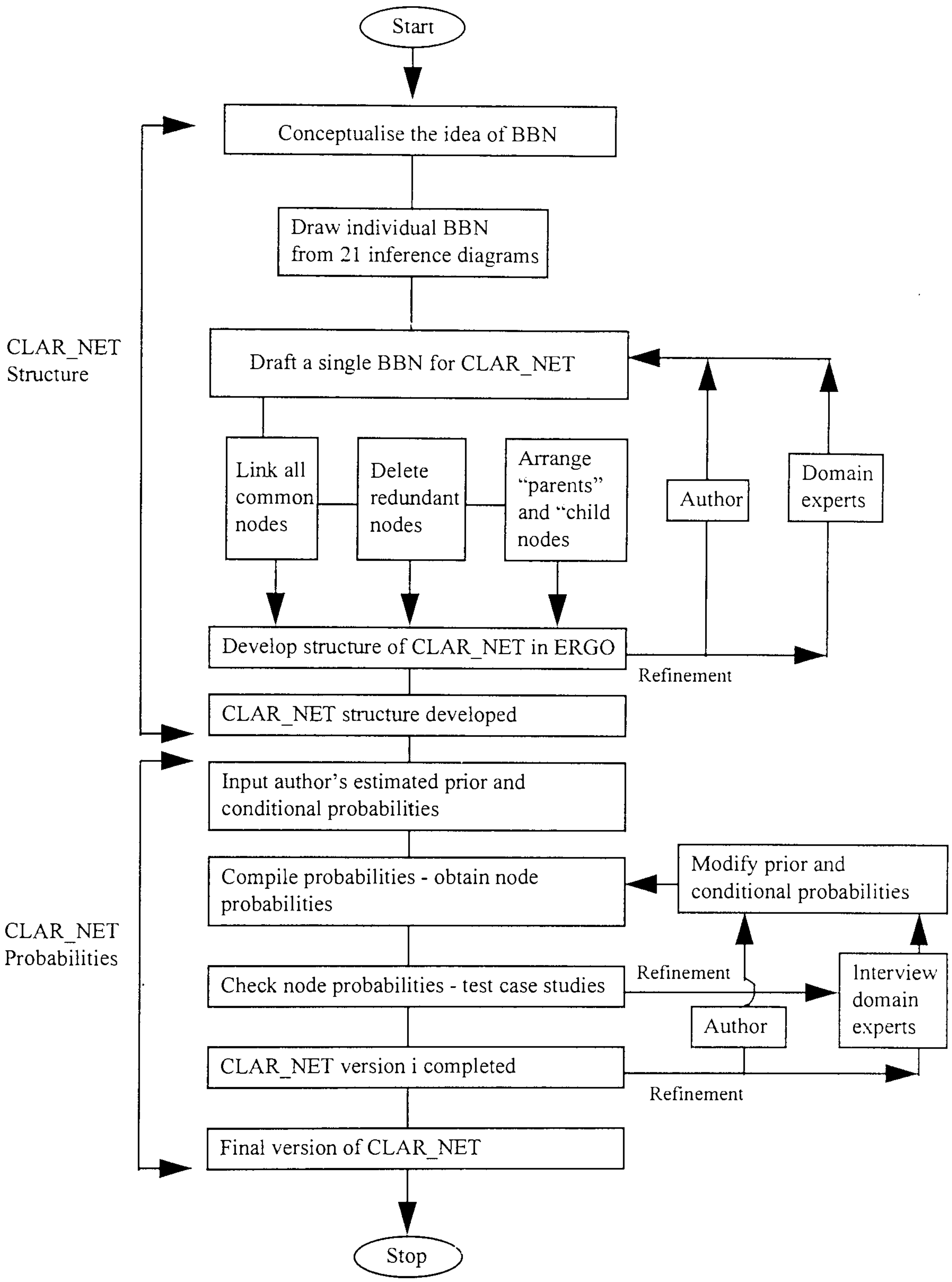

Figure 5.1 A flow diagram showing the stages in development of CLAR_NET

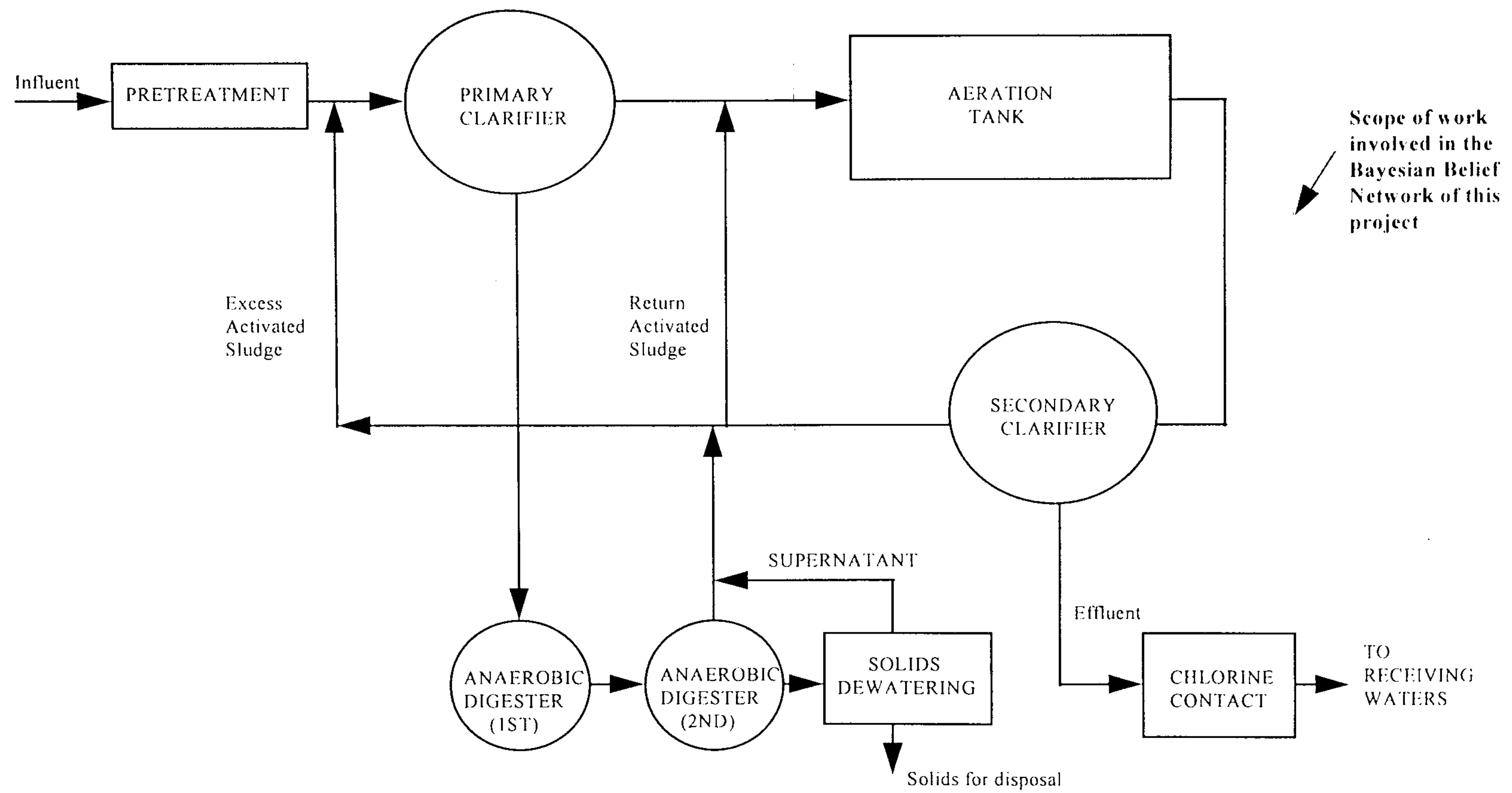

Figure 5.2 Layout of a Typical Wastewater Treatment System. The system within the dotted-lines indicate the scope of CLAR_NET.

5.2 The Structure of CLAR_NET

Since a BBN's structure is basically a representation of cause-effect relationships, the initial attempt to develop the structure of CLAR_NET focussed on ways to inter-connect all the causal relationships ("symptoms" and "possible causes") of the 21 inference diagrams (as shown in Appendix A) previously derived for CLAR_EX. Unfortunately, both the task and the structure was found to be too complicated.

It was subsequently realized that this seemingly complicated task could be overcome by cutting it into smaller steps. Thus, each of the inference diagrams was converted into a belief network structure, with a "symptom" node representing the "child" which linked to the "possible causes" nodes representing the "parents". Examples of these networks are shown in Figures 5.3 and 5.4.

The next task was to combine all the individual networks into a single BBN. Since the activated sludge treatment process is a dynamic and cyclic operation where at times there exists a vicious circle between "symptoms" and "causes", it was sometimes difficult to clearly distinguish which entity should be the parent and which the child. For example: septic sludge is caused by low "DO", but it could be argued also that low "DO" is caused by the presence of septic sludge in the system; low rate of sludge pumping (low "PumpingRate") causes low volume sludge abstraction rate (low "VolSldgAbsRt"), but the reverse could also be true. Fortunately, the ability of BBNs to reason bi-directionally enables the above problem to be resolved.

The other challenge was to logically arrange the nodes so that there was a sequential flow from "parent" to "child" nodes. Since most of the clarifier problems which occur in clarifiers eventually cause excess solids to flow over the weirs ("SolidOvrWeir"), there is a tendency to point all the nodes to the "SolidOvrWeir" node. As a result, the "SolidOvrWeir" node had nine parents at one point in time. Thus, its parents had three possible states, it would be necessary to elicit almost 20,000 conditional probabilities for this one node alone. This would not only result in the formation of a large clique, but also undermine the computational advantage associated with the belief propagation algorithm. The solution to this potential problem was to examine again all the nine immediate "parents" of the "SolidOvrWeir" node, and classed some of them as "grandparents" or "great-grandparents" by introducing intermediate common relatives. That is, the true causal relationships involved were defined at a finer level of granularity.

Another essential features of a BBN is that descriptive terms for each entity need not be presented. For instance, low aeration rate may cause problems such as septic sludge, but high aeration may cause some problems too, like deflocculation. In the inference diagrams, these two parameters were drawn as two separate nodes: "low aeration rate", and "high aeration rate". However, since each node in the belief network was able to denote various states of the entities it represents, low and high aeration could be represented with one node called Aeration, thus the diagram was condensed during the refinement process.

In essence, the main task of developing the CLAR_NET structure started from the author's knowledge on wastewater treatment process. Subsequent knowledge were elicited from a domain expert in wastewater treatment, Mr. P. Nungessor of the Bureau of Pollution in Atlanta, USA and the structure went through a few rounds of refinement as a result of Mr. Nungessor's input. Another domain expert, Mr. H.A. Hawkes of Aston University was sought for his comments on the refined structure to ensure the causal relationship between the nodes are properly represented in CLAR_NET. Subsequent refinements were made after another few rounds of comments by both the experts.

The CLAR_NET structure as shown in Figure 5.5 is a result of many rounds of refinement. It is a prototype depicting the susbsystem for an actual activated sludge process in wastewater treatment, and can be easily modified to suit the characteristics and requirements of any treatment plant.

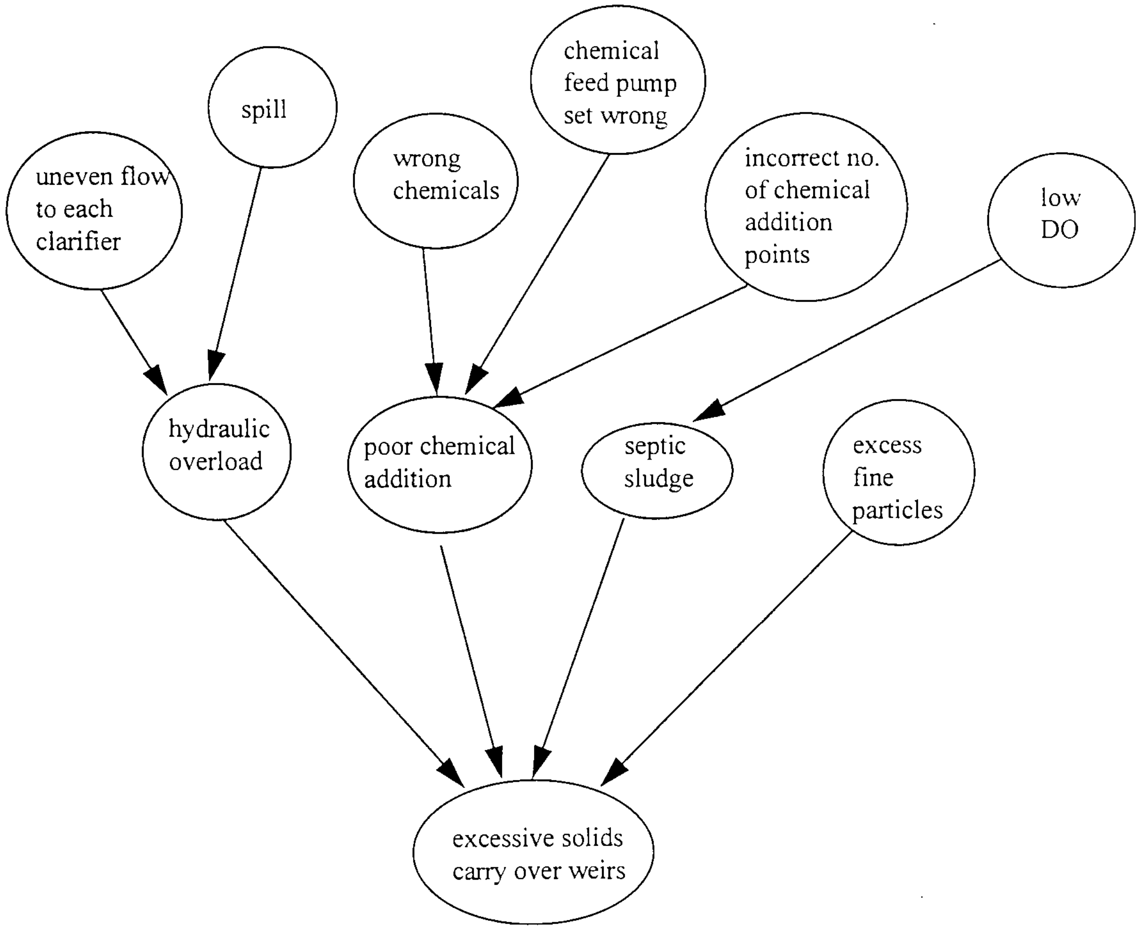

Figure 5.3 A typical individual causal network (shown here for "excessive solids carry over weirs") drawn from the inference diagrams before linking to other nodes to form CLAR_NET.

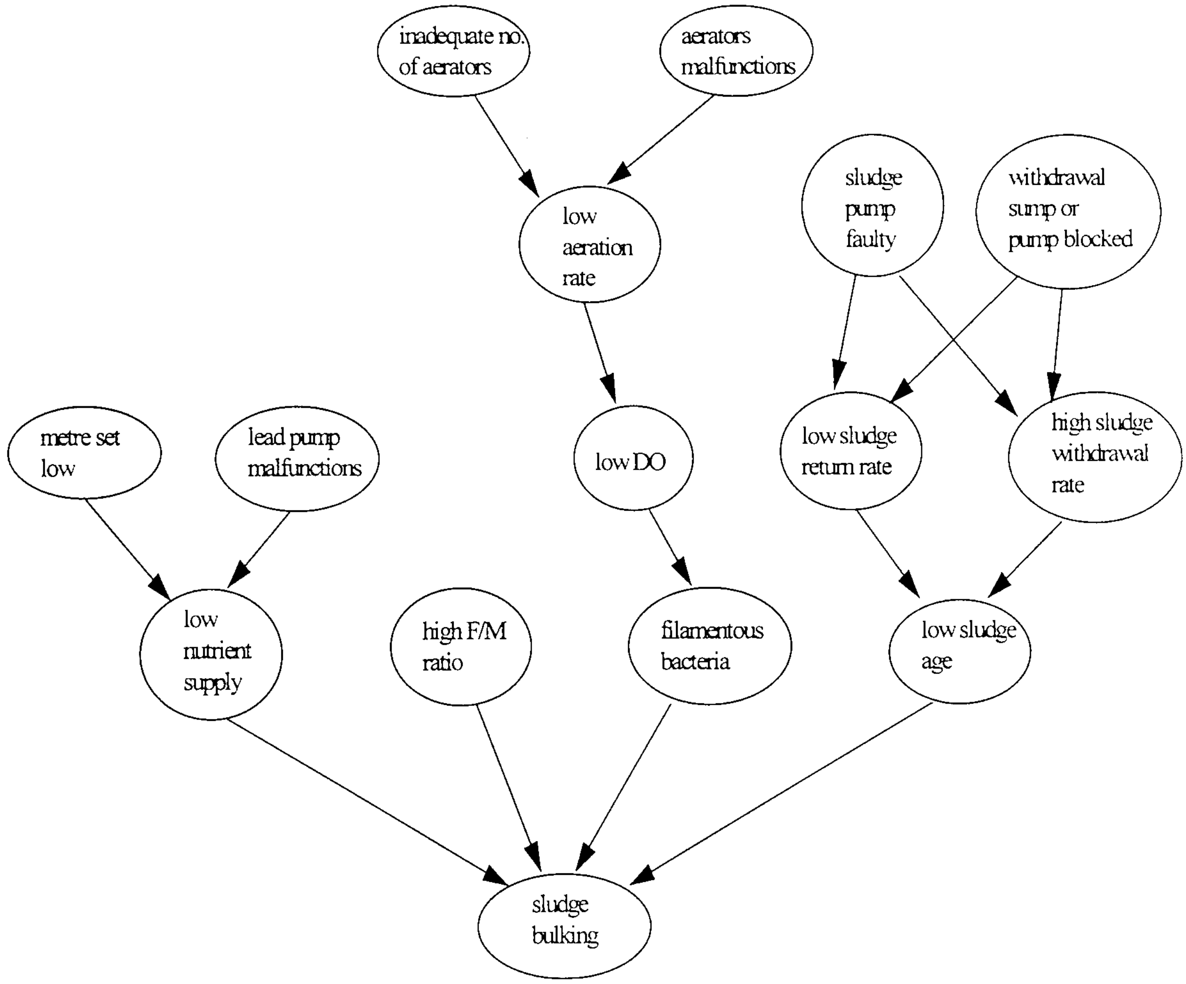

Figure 5.4 Another example of individual BBN (shown here for "sludge bulking") drawn before linking to other nodes to form CLAR_NET

5.3 Node Probabilities of CLAR_NET

5.3.1 States of Entities

Each node in the network has 2 or 3 possible states, for example, most of the operating parameters such as Dissolved Oxygen ("DO"), aeration rate ("Aeration"), C:N:P ratio ("CNPRatio") have three possible states: "low", "normal" and "high" or "excess". The state "normal" refers to the state under normal operating conditions. For example, the normal rate of DO is 2 mg/l to 4 mg/l, and below 2 mg/l is considered "low", and above 4 mg/l is considered "high". However, most of the parameters that can be observed have just two states: "present" and "absent". For instance, oil is considered as "present" if there are visible signs of it on top of the wastewater. Clearly, the borderline between "present" and "absent" is rather vague and largely depends on personal judgment.

A complete list of the various states for all the nodes in CLAR_NET is given in Table 5.1.

5.3.2 Elicitation and Input of Probabilities

The prior and conditional probabilities of each node in CLAR_NET were initially derived according to the best judgment of the author and then input into the network.

An important assumption made in the derivation of the prior and conditional probabilities was that the prior condition of the system represents the normal state of a well-run wastewater treatment system. In other words, there is a high probability (at least 90%) that the activated sludge system is performing normally. This requirement was an important consideration when selecting the initial conditional probabilities. For example, "Aeration", which has 3 states: "low", "normal", and "high", has prior probabilities of 0.03, 0.95, 0.02 respectively. The same applies for other "first generation" nodes such as "Pretreatment" where the prior probabilities for "good" and "poor" conditions are 0.95 and 0.05 respectively. The numbers (>0.90 for normal functioning) chosen by the author as being a reasonable estimate of the likelihood of normal functioning of the components, and there is no set rule to say whether the prior probability of 0.90 for "good" pretreatment is more realistic than say 0.85 or 0.95, for example.

For nodes that involve "parental" relationships, the input of the required probabilities was more complicated. For example, "VolSldgAbsRt" has "PumpingRate", "Outlet", and "Scraper" as "parents", so the probability of it being in any given state is conditioned by the known or likely state of each of its three parents. Thus, the probability of each of its possible states has to be estimated for each possible combination of the states of three parents. This calls for a lot of judgement. The numbers selected were input such that there was a gradual change in probabilities as the "intensity" of each state changed. Tables 5.2 and 5.3 show two such examples.

The probabilities were entered into CLAR_NET based initially on the author's knowledge. The network was then compiled and run to give the prior (that is "no evidence") beliefs in the states of all nodes. Examination of the results showed that some nodes had relatively high beliefs in abnormal states, contrary to what one would expect.

The next stage was to re-examine all the conditional probabilities and where possible modified them to reduce the likelihood of indicating abnormal prior beliefs. Then the results produced were then presented to one of the domain experts, Mr. P. Nungesser for comments. Refinements were then made and the results were commented by the second expert, Mr. H.A. Hawkes.

By careful and successive adjustments, a network was constructed in which the prior belief in the normal functioning of each node was greater than 90%. The only exception to this was the "Influent Type" node whose three states were: industrial, domestic and mixed industrial/domestic. The concept of normal operation clearly did not apply to this node.

The CLAR_NET network was then tested to ensure accuracy. The results were evaluated and the prior and conditional probabilities were modified as necessary. The methodology and results of the tests will be presented in the next chapter.

Table 5.1 A list of states of conditions for all nodes in CLAR_NET

No	Node	Possible States	Parents
1	AccuSludge	Low Normal Excess	SludgeAccuRt, VolSldgAbsRt
2	Aeration	Low Normal High	
3	Agitation	Low Normal High	Aeration
4	BOD	Low/Normal High	InfluentType, Spill
5	Baffle	Good Faulty	
6	Bulking	Yes No	FilBact_A, SludgeAge
7	CNPRatio	Low Normal High	N_Load, P_Load, BOD
8	DO	Low Normal High	Aeration
9	Defloc	Yes No	Agitation, pH, ToxicWaste
10	Denitrify	Yes No	SepticSludge
11	DetentTime	Short Normal Long	HydLoad
12	DispGrowth	Yes No	DO, BOD, Defloc
13	Effl_Ammonia	Normal High	DO, pH
14	Effl_BOD	Low/Normal High	SolidOvrWeir, OrganicLoad, ToxicWaste
15	Effl_Nitrate	Normal High	Denitrify, DO
16	ExcessFoam	Yes No	Nocardia, Surfactant
17	FMRatio	Low Normal High	OrganicLoad
18	FilBact_A	Present Absent	FMRatio, CNPRatio, DO
19	FilBact_B	Present Absent	FMRatio, CNPRatio, Nocardia
20	FloatSludge	Yes No	InaFloatable, RisingSludge
21	HydLoad	Low Normal High	Spill, Pretreatment
22	InaFloatable	Yes No	Pretreatment
23	InfluentType	Industrial Domestic Mixed	
24	MassSettRate	Low Normal High	Bulking, HydLoad
25	Mousse	Yes No	FilBact_B
26	N_Load	Low Normal High	
27	Nocardia	Present Absent	
28	NonFloc	Yes No	TurbidWaste
29	Oil	Present Absent	Pretreatment
30	OrganicLoad	Low Normal High	BOD, HydLoad
31	Outlet	Free Blocked	
32	P_Load	Low Normal High	
33	PinFlóc	Present Absent	Agitation, DO, SludgeAge
34	Pretreatment	Good Poor	
35	PumpingRate	Low Normal High	
36	RASRate	Low Normal High	
37	RisingSludge	Yes No	Denitrify, Oil, Mousse
38	Scraper	Normal Abnormal	
39	SepticSludge	Present Absent	DO, OrganicLoad, VolSldgAbsRt
40	ShortCircuit	Yes No	Baffle, Weir, HydLoad
41	SludgeAccuRt	Low Normal High	OrganicLoad, MassSettRate, FloatSludge, TurbidSusp
42	SludgeAge	Low Normal High	FMRatio, RASRate
43	SludgeConct	Low/Normal High	AccuSludge
44	SolidOvrWeir	Yes No	ShortCircuit, MassSettRate, AccuSludge, TurbidSusp, FloatSludge
45	Spill	Yes_Toxic Yes_NonToxic No	
46	Surfactant	Present Absent	
47	ToxicWaste	Yes No	Spill, InfluentType
48	TurbidSusp	Yes No	DispGrowth, NonFloc, PinFloc
49	TurbidWaste	Present Absent	
50	VolSldgAbsRt	Low Normal High	PumpingRate, Outlet, Scraper
51	Weir	Level Not_Level	
52	pH	Neutral Low_High	

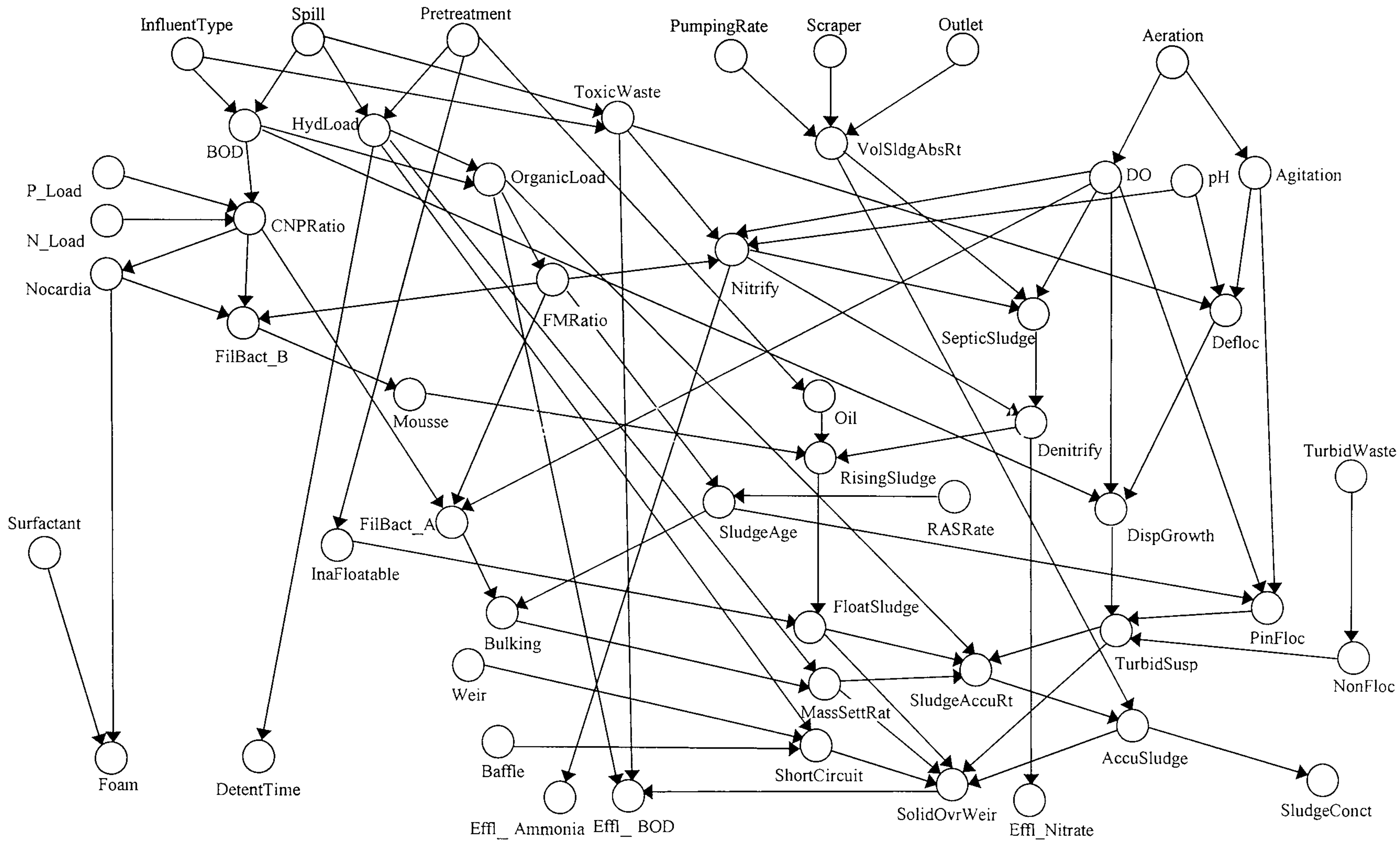

Figure 5.5 Structure of CLAR_NET for diagnosis of faults in an activated sludge system of wastewater treatment plant

Table 5.2 Probabilities input into the node "VolSldgAbsRt"

	Scraper	Norm	Norm	Norm	Norm	Norm	Norm	Abn	Abn	Abn	Abn	Abn	Abn
	Pumping Rate	Low	Low	Norm	Norm	High	High	Low	Low	Norm	Norm	High	High
	Outlet	Free	Blocked	Free	Blocked	Free	Blocked	Free	Blocked	Free	Blocked	Free	Blocked
Low		0.20	0.70	0.01	0.50	0.01	0.20	0.25	0.75	0.1	0.55	0.1	0.5
Normal		0.79	0.29	0.98	0.49	0.69	0.70	0.74	0.24	0.89	0.44	0.7	0.49
High		0.01	0.01	0.01	0.01	0.30	0.10	0.01	0.01	0.01	0.01	0.2	0.01

Where, Abn = Abnormal, Norm = Normal

Table 5.3 Conditional probabilities for node "Defloc"

	ToxicWaste	Yes	Yes	Yes	Yes	No	No	No	No
	Agitation	Normal	Normal	Excess	Excess	Normal	Normal	Excess	Excess
	pH	Normal	Low	Normal	Low	Normal	Low	Normal	Low
Yes		0.10	0.35	0.55	0.80	0.01	0.10	0.30	0.40
No		0.90	0.65	0.45	0.20	0.99	0.90	0.70	0.60

Chapter 6 PERFORMANCE ASSESSMENT OF THE BELIEF NETWORK

6.1 Objective

The work described in this chapter aimed to assess whether CLAR_NET could provide accurate diagnosis and prediction of faults in an activated sludge system. Results of the predictions are compared to predictions made by human experts, with a view to testing the accuracy of CLAR_NET.

6.2 Assessment Methodology

To evaluate the performance of CLAR_NET, an assessment methodology was devised. The procedure is summarized below.

1. Examination of CLAR_NET's prior probabilities for the "no evidence" case

   CLAR_NET was tested under the normal plant operating condition, when no problem occurs in the activated sludge system. This test was necessary to determine how CLAR_NET will perform under the normal condition, as compared to its behaviour under abnormal condition. Each node's probabilities were checked to see if they were indicating a high probability ($\geq$90%) of the "normal" state.

2. Tests based on possible problem cases in wastewater treatment system

   Various cases, with different known evidence, were used on CLAR_NET to find the effects of such evidence on the rest of the system. The purpose of the exercise was to determine whether CLAR_NET could respond well under the influence of different operating conditions and/or known symptoms.

3. Sensitivity test on CLAR_NET

   CLAR_NET was tested to check its sensitivity to evidence, or when additional evidence is presented at various nodes, acting singly or in addition to other evidence. The tests should also demonstrate the stability of the system, whereby those nodes which should be insensitive to the evidence would indeed be insensitive.

4. <u>Comparison of results from CLAR_NET with responses from domain experts</u>

   Prediction made by domain experts based on various possible cases of wastewater operations were obtained from their responses to pre-set questionnaires. Each question in the questionnaire was representative of the actual problem occurring in the activated sludge wastewater treatment plant. The results from CLAR_NET based on these same cases were compared to those predicted by the human domain experts. The overall performance of CLAR_NET was then estimated based on the outcome of these comparisons.

Details of the processes involved in the above methodology are described in the following sections.

6.3 Running CLAR_NET with "No Evidence"

This was the first step in determining the network's ability to predict results accurately. The "no evidence" condition assumed that all the operating conditions were working normally. The probabilities for all the nodes were evaluated. The criterion for accepting the results was that the probabilities for the normal state for each node should be more than 90%. As noted in Chapter 5, this requirement (≥ 90%) was considered a reasonable likelihood of normal functioning of the wastewater treatment system.

For example, the simulated results gave the probability for the absence of Nocardia as 96%. This means that if the activated sludge system was working well, Nocardia would most likely be absent (96%).

Table 6.1 lists all the node probabilities for the "no evidence" case. The results indicated all the node probabilities for "normal" or "good" conditions were in the 90-100% range, which satisfies the criterion set for this test. The only exceptions were the "OrganicLoad" and "FMRatio" nodes, where the probabilities for "normal" condition were below 90%, but the combined "low" and "normal" conditions were 89.6% and 93.5%, good enough to be considered in the range of 90%.

Table 6.1 Node probabilities for the "No Evidence" condition

Node	State of Condition	Probabilities
AccuSludge	Low Normal Excess	0.020977 0.923628 0.055428
Aeration	Low Normal High	0.030002 0.950050 0.020001
Agitation	Normal Excess	0.938247 0.061803
BOD	Normal High	0.948575 0.051478
Baffle	Good Faulty	0.950050 0.050003
Bulking	Yes No	0.061932 0.938121
CNPRatio	Low Normal High	0.025714 0.916107 0.058231
DO	Low Normal High	0.029201 0.950048 0.020801
Defloc	Yes No	0.038374 0.961666
Denitrify	Normal Abnormal	0.900626 0.099427
DetentTime	Short Normal Long	0.059874 0.910590 0.029567
DispGrowth	Yes No	0.069041 0.931004
Effl_Ammonia	Normal High	0.920624 0.079417
Effl_BOD	Normal High	0.902280 0.097771
Effl_Nitrate	Low/Normal High	0.911505 0.088548
FMRatio	Low Normal High	0.149029 0.785754 0.065256
FilBact_A	Present Absent	0.038990 0.961061

Table 6.1 (continued) Node probabilities for the "No Evidence" condition

Node	State of Condition	Probabilities
FilBact_B	Present Absent	0.038786 0.961267
FloatSludge	Present Absent	0.089556 0.910497
Foam	Normal Excess	0.936484 0.063569
HydLoad	Low Normal High	0.030527 0.909748 0.059778
InaFloatable	Yes No	0.080004 0.920049
InfluentType	Industrial Domestic Mixed	0.550029 0.200011 0.250013
MassSettRate	Low Normal High	0.036562 0.951994 0.011498
Mousse	Yes No	0.034824 0.965229
N_Load	Low Normal High	0.030002 0.950049 0.020001
Nitrify	Normal Abnormal	0.912172 0.087869
Nocardia	Present Absent	0.039476 0.960577
NonFloc	Yes No	0.080004 0.920046
Oil	Present Absent	0.087505 0.912548
OrganicLoad	Low Normal High	0.245569 0.650877 0.103582
Outlet	Free Blocked	0.950030 0.050001
P_Load	Low Normal High	0.030002 0.950049 0.020001
PinFloc	Present Absent	0.051612 0.948422
Pretreatment	Good Poor	0.950050 0.050003

Table 6.1 (continued) Node probabilities for the "No Evidence" condition

Node	State of Condition	Probabilities
PumpingRate	Low Normal High	0.040001 0.950030 0.010000
RASRate	Low Normal High	0.040002 0.950046 0.010000
RisingSludge	Yes No	0.088885 0.911168
Scraper	Normal Abnormal	0.950030 0.050001
SepticSludge	Present Absent	0.085955 0.914094
ShortCircuit	Yes No	0.049695 0.950358
SludgeAccuRt	Low Normal High	0.039823 0.910740 0.049484
SludgeAge	Low Normal High	0.027625 0.944656 0.027767
SludgeConct	Normal High	0.906528 0.093505
SolidOvrWeir	Yes No	0.051919 0.948133
Spill	Yes_Toxic Yes_NonToxic No	0.025001 0.025001 0.950049
Surfactant	Present Absent	0.050003 0.950050
ToxicWaste	Yes No	0.054890 0.945162
TurbidSusp	Yes No	0.078005 0.922046
TurbidWaste	Present Absent	0.050003 0.950048
VolSldgAbsRt	Low Normal High	0.067681 0.925146 0.007205
Weir	Level Not-Level	0.950050 0.050003
pH	Normal Abnormal	0.950038 0.050002

6.4 Tests based on Possible Problem Cases in Wastewater Treatment Systems

This exercise aimed to test the behaviour of CLAR_NET under several problems that could possibly occur in an activated sludge system of a wastewater treatment plant. This would also effectively determine whether CLAR_NET could be used as a reliable tool to diagnose the possible causes or predict possible impacts in such a plant, as well as to illustrate the bi-directional propagating properties inherent in CLAR_NET which is a belief network.

Table 6.2 shows 40 of such cases conducted. There are 23 numbers of predictive cases and 17 numbers of diagnostic cases made, as indicated by "P" and "D" respectively in the "Type of Questions" column. Predictive questions means given the evidence (say Dissolved Oxygen level is low), how would that impact on the output (say, septic sludge is present) as in Question 1. Diagnostic questions would involve finding out the possible causes of occurrence, say having observed excess solids flowing over the weirs, what would be the likelihood that the outlet pipe is blocked (as in Question 15)?

In the actual wastewater treatment system, the operator may have little evidence that would help him to analyse the possible causes or effects. A good mix of cases were presented in Table 6.2, some with one item of evidence, some with two or three. There are a number of questions with a single evidence to find the known causes or effects, this could check the response from CLAR_NET is able to show a change of its percentage of occurrence as compared to the "No Evidence" case. Then the cases were made more complicated by introducing one or two additional pieces of evidence.

For example in Question 1, if the dissolved oxygen in the mixed liquor is low, then CLAR_NET predicts the possibility of septic sludge as 56.80%. However, when there is additional evidence that the outlet pipe is blocked (as in Question 3), CLAR_NET's prediction of septic sludge increases to 73.00%. This is in agreement with the normal prediction of human experts, whereby additional supporting evidence strengthens their belief in the suspected cause, such as the presence of septic sludge in the above case. The percentage change from the "No Evidence" case has also been increased as expected, from 48.20% (in Question 1) to 64.40% (in Question 3).

Table 6.2 Results of test cases using CLAR_NET

No.	Evidence Obtained	Desired Information	CLAR_NET Results (%)			Type* of Questions
			With Evidence (A)	"No Evidence" (B)	Changes in Probability (A-B)	
1	"DO": low	Septic sludge: present?	56.80	8.60	48.20	P
2	"Outlet": blocked	Septic sludge: present?	17.30	8.60	8.70	P
3	"DO": low, "Outlet": blocked	Septic sludge: present?	73.00	8.60	64.40	P
4	"RASRate": low	Pin floc: present?	17.11	5.16	11.95	P
5	"RASRate": normal, and "FMRatio":high	Pin floc: present?	8.30	5.16	3.14	P
6	"RASRate": low, and "FMRatio":high	Pin floc: present?	29.86	5.16	24.70	P
7	"Spill": toxic	Deflocculation : present?	13.60	3.84	9.76	P
8	"Spill": toxic, "pH": low, "Aeration": high	Deflocculation : present?	61.70	3.84	57.86	P
9	"Spill":toxic, "OrganicLoad": normal	Effluent BOD: high?	39.50	9.78	29.72	P
10	"Spill": toxic, "OrganicLoad": high	Effluent BOD: high?	87.60	9.78	77.82	P
11	"SolidOvrWeir": excess, "ToxicWaste": present	Effluent BOD: high?	93.60	9.78	83.82	P
12	"SludgeAge": high	Pin floc: present?	47.20	5.16	42.04	P
13	"InfluentType": industrial waste	Effluent BOD: high?	10.10	9.78	0.32	P
14	"Nutrient": low Nitrogen, "DO": low	Filamentous bacteria A: present?	61.50	3.90	57.60	P

Table 6.2 (Continued) Results of test cases using CLAR_NET

No	Evidence Obtained	Desired Information	CLAR_NET Results (%)			Type* of Questions
			With Evidence (A)	"No Evidence" (B)	Changes in Probability (A-B)	
15	"SolidOvrWeir": excess	Outlet: blocked?	6.80	5.00	1.80	D
16	"SolidOvrWeir"	Effluent BOD: high?	71.80	9.78	62.02	P
17	"Scraper" : malfunction	Excess solids over weir?	92.20	5.19	87.01	P
18	"DO": low	Dispersed growth: present?	41.10	6.90	34.2	P
19	"TurbidSusp": yes	Pin floc": present?	45.60	5.16	40.44	D
20	"HydLoad": high	Detention time" short?	90.00	5.99	84.01	P
21	"Foam": excess	Influent BOD: normal?	95.60	94.85	0.75	D
22	"SolidOvrWeir": excess	Organic load: high?	16.57	10.36	6.22	D
23	"SolidOvrWeir": excess, and "Effl_BOD": high	Organic load: high/	21.24	10.36	10.89	D
24	"Effl_BOD": high	Sludge pumping rate: abnormal?	5.20	5.00	0.20	D
25	"Effl_Nitrate": high	Denitrification: abnormal?	89.80	9.94	79.86	D
26	"Effl_BOD": high	Hydraulic load: abnormal?	17.30	9.03	8.27	D
27	"FloatSludge": present	Aeration rate: abnormal?	7.20	5.00	2.20	D

Table 6.2 (Continued) Results of test cases using CLAR_NET

Case	Evidence Obtained	Desired Information	CLAR_NET Results (%)			Type* of Questions
			With Evidence (A)	"No Evidence" (B)	Changes in Probability (A-B)	
28	"Oil": present	Pretreatment: poor?	45.70	8.75	36.95	D
29	"AccuSludge": excess	Volume sludge abstraction rate: low?	62.20	6.77	55.43	D
30	"PinFloc": present	Agitation due to aerators: excess?	55.10	6.18	48.92	D
31	"SludgeAge": high	Turbid suspension: yes	35.07	7.80	24.73	P
32	"HydLoad": high	Solid over weirs: excess	13.75	5.19	8.56	P
33	"InfluentType": Industrial	Sludge age: low	2.80	2.76	0.04	P
34	"Effl_Ammonia": high	Toxic waste: yes	31.27	5.49	25.78	D
35	"Agitation": excess	Solid over weirs: excess	5.88	5.19	0.69	P
36	"Foam": excess, and "RisingSludge": yes	Filamentous bacteria: present?	31.53	3.88	27.65	D
37	"Effl_Nitrate": high and "Effl_Ammonia: high	Septic sludge: present?	42.70	8.59	34.11	D
38	"TurbidSusp": high and "Effl_Ammonia: high	pH: abnormal?	11.80	5.00	6.8	D
39	"Bulking": yes and "Effl_Nitrate": high	F/M Ratio: high?	9.42	6.53	2.89	D
40	"ToxicWaste": present and "SolidOvrWeir": excess	Rising sludge: yes	24.79	8.89	15.90	P

* "D" indicates diagnostic type of question, whereas "P" indicates predictive type.

Similar trends were shown in the responses received for other "predictive" questions such as in Questions 4 to 6, and Questions 7 to 11. In Question 4, with low return activated sludge rate ("RASRate"), the presence of pin floc is 17.11%, and an additional evidence of high "FMRatio" in Question 6 has increased the probability to 29.86%. The "diagnostic" questions show similar results. In Questions 22 and 23 for example, when additional evidence of high effluent BOD ("Effl_BOD") is introduced, the probability of occurrence of high organic load in the influent is increased from 16.57% to 21.24%.

Most of the nodes within CLAR_NET were tested to ensure they fall within the expected range of results. The results were generally found to be acceptable within the range of the author's expectation. The above tests indicated CLAR_NET is able to perform both diagnostic and predictive reasoning about relationships within the wastewater system.

6.5 Sensitivity Tests on CLAR_NET

Nine representative test cases are presented here to demonstrate the sensitivity and stability of CLAR_NET with respect to the evidence presented. These cases with the evidence received are summarized below. Case 9 is used as a "control" case where the probabilities served as the basis for other cases to compare.

Case 1: "Spill" occurs and is toxic.

Case 2: "Agitation" of the aerators is excessive.

Case 3: "DO": low (that is, Dissolved Oxygen of the mixed liquor is too low).

Case 4: "DO" low and "Outlet" pipe is blocked.

Case 5: "DO" low and Nitrogen nutrient ("N_Load") was low.

Case 6: "DO" low and "Spill" occurs and is toxic.

Case 7: Solids flowing over the weirs of clarifiers ("SolidOvrWeir") is excessive.

Case 8: "SolidOvrWeir" is low and toxic waste ("ToxicWaste") is present.

Case 9: No evidence case.

For each of the above cases, all the nodes in CLAR_NET that are *d-connected* with the evidence node or nodes were examined. (Refer to Chapter 4 for explanation *on d-connection* and *d-separation*). The following details the test conducted for each case.

In analysing the test results for each case, the d-connected nodes in CLAR_NET were colour-coded to illustrate the impact of the evidence (that is, the difference in probability for a particular node under the test case and the "No Evidence" case). Figure 6.1 shows the notation for colours used for the all the test cases here.

Case 1 : "Spill": yes_toxic

To study the impacts when CLAR_NET received the evidence that toxic spill ("Spill": yes_toxic) had occurred, those nodes which are *d-connected* to the "Spill" node are identified using the procedure described in Chapter 4. These *d-connected* nodes within CLAR_NET are shaded as shown in Figure 6.2. These are the only nodes which are affected by evidence presented at the "Spill" node, the other nodes being independent of "Spill" under the given conditions (that is, no other evidence).

When evidence is presented at the "Spill" node, the probability of occurrence of the d-connected changed to a greater or lesser degree. Table 6.3 presents the results of such an operation. It compares the probability under the "No Evidence" case with that resulting from the introduction of evidence that toxic spill occurs (Case 1). The difference in the probability (Cases 1 to 9) were also shown in Table 6.3.

Figure 6.3 shows the effects on the *d-connected* nodes in a colour coded format to indicate the magnitude of the change in probability (that is, the node probability for Case 1 to Case 9). The key to the colour code is shown in Figure 6.1.

The results indicate that when toxic spill occurs in the wastewater treatment system, there is a high probability of the toxic waste being present (86.51%, an increase of 81.02% as shown in the "Change in probability" column of Table 6.3, and shown coloured blue in Figure 6.3 to illustrate the magnitude of change) as expected. There were other major changes in probability such as high hydraulic load ("HydLoad") and short detention time of the mixed liquor ("DetentTime") of 60.04% and 53.82% respectively; and these nodes are coloured green in Figure 6.3. Subsequent impacts on high "BOD", high "OrganicLoad", abnormal nitrification ("Nitrify") and high effluent Ammonia ("Effl_Ammonia") are noted with the changes in probabilities between 30-50%, and coloured brown on Figure 6.3. Smaller impacts (10-30%)

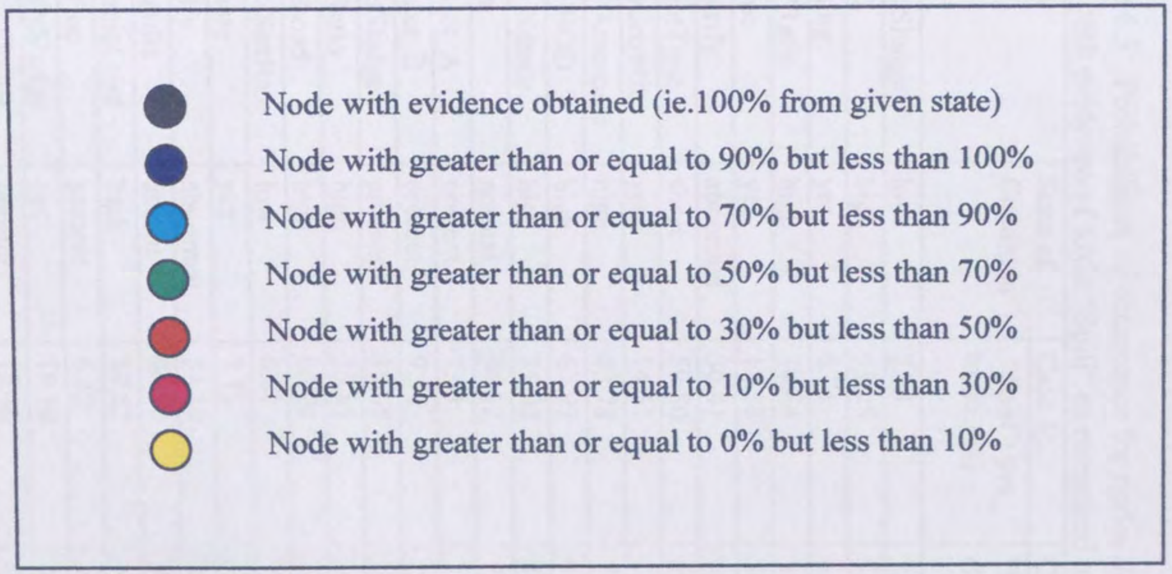

Figure 6.1 Notation for the colour of the nodes showing the magnitude of influence for all the “sensitivity test cases in Section 6.5.

shown in pink for other *d-connected* nodes are registered for high "CNPRatio", high "FMRatio", presence of "RisingSludge", abnormal "Denitrification", high "Effl_Nitrate" and low sludge concentration ("Sludge_Cont").

The impacts on the *d-connected* nodes in Figure 6.3 clearly illustrate the magnitude of the sensitivities of the nodes of the CLAR_NET network in response to the evidence that toxic spill has occurred.

Table 6.3 Probabilities of occurrence for nodes *d-connected* to the "Spill" node with evidence of toxic "Spill" as compared to the "No Evidence" case

Node	State of Condition	Case 1 "Spill": yes_ toxic (%)	Case 9 "No Evidence" (%)	Change in probability (Case 1 - Case 9) (%)
AccuSludge	low	2.63	2.10	0.53
BOD	high	53.25	5.15	48.10
Bulking	yes	6.75	6.19	0.56
CNPRatio	high	30.84	5.82	25.02
Defloc	yes	12.58	3.84	8.74
Denitrify	abnormal	30.41	9.94	20.47
DetentTime	short	59.80	5.98	53.82
DispGrowth	yes	14.51	6.90	7.61
Effl_Ammonia	high	43.74	7.94	35.80
Effl_BOD	high	67.97	9.78	58.19
Effl_Nitrate	high	25.02	8.85	16.17
Foam	normal	94.12	93.64	0.48
FilBact_A	present	7.01	3.90	3.11
FilBact_B	present	9.58	3.88	5.70
FloatSludge	present	15.65	8.95	6.70
FMRatio	high	35.81	6.53	29.28
HydLoad	high	66.01	5.97	60.04
MassSettRate	low	6.51	3.66	2.85
Mousse	yes	7.13	3.48	3.65
Nitrify	abnormal	54.10	8.79	45.31
Nocardia	absent	96.76	96.08	0.71
OrganicLoad	high	59.52	10.36	49.16
PinFloc	present	6.42	5.16	1.26
RisingSludge	yes	19.39	8.89	10.50
SepticSludge	present	15.40	8.60	6.80
ShortCircuit	yes	16.14	4.97	11.17
SludgeAccRate	high	23.02	4.95	18.07
SludgeAge	high	5.67	2.78	2.89
SludgeConct	high	12.73	9.35	3.38
SolidOvrWeir	yes	10.78	5.19	5.59
Spill	**yes_toxic**	**100.00**	**2.50**	**97.50**
ToxicWaste	yes	86.51	5.49	81.02
TurbidSusp	yes	11.01	7.80	3.21

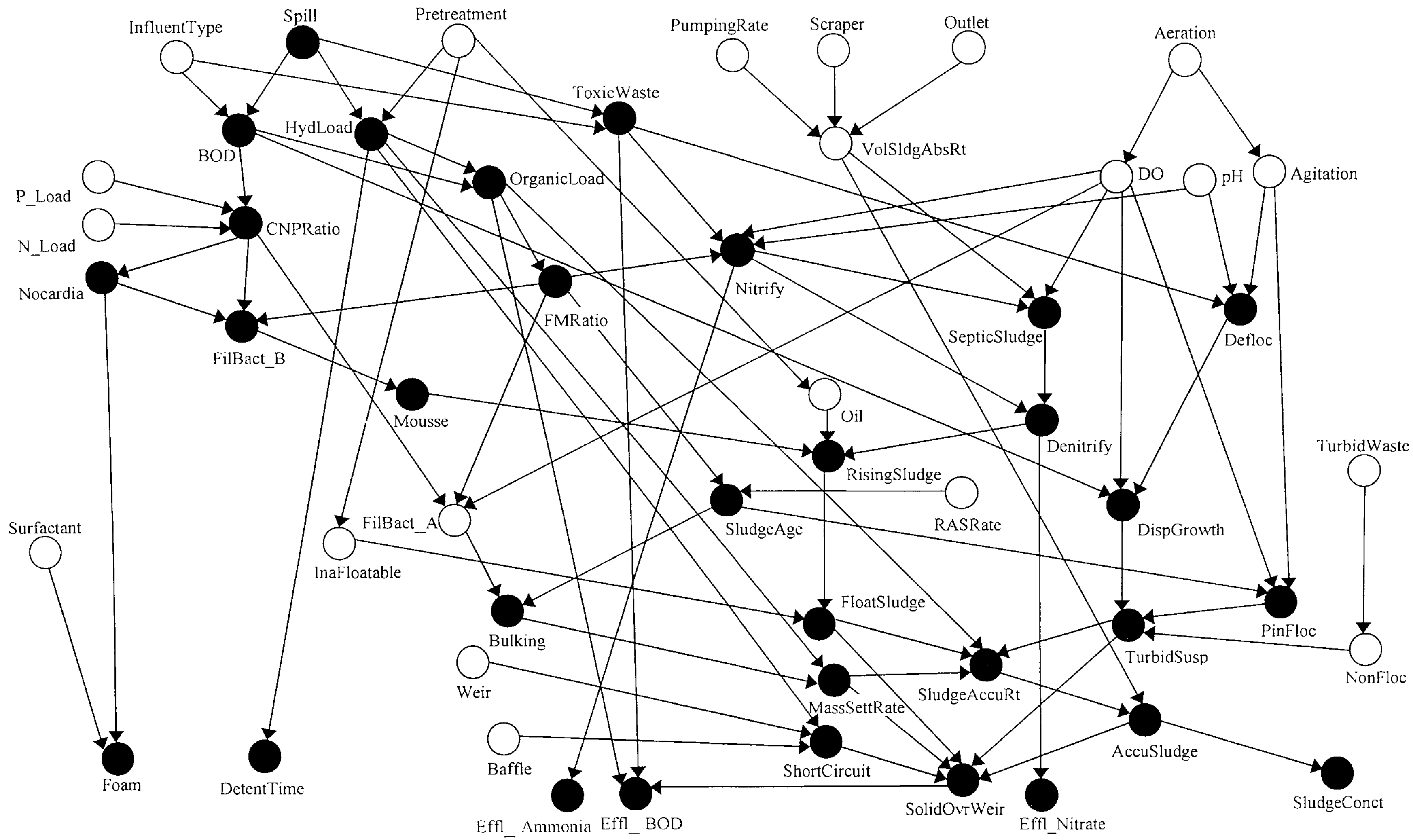

Figure 6.2 Node *d-connected* to “Spill” node are shaded for study in Test Case 1.

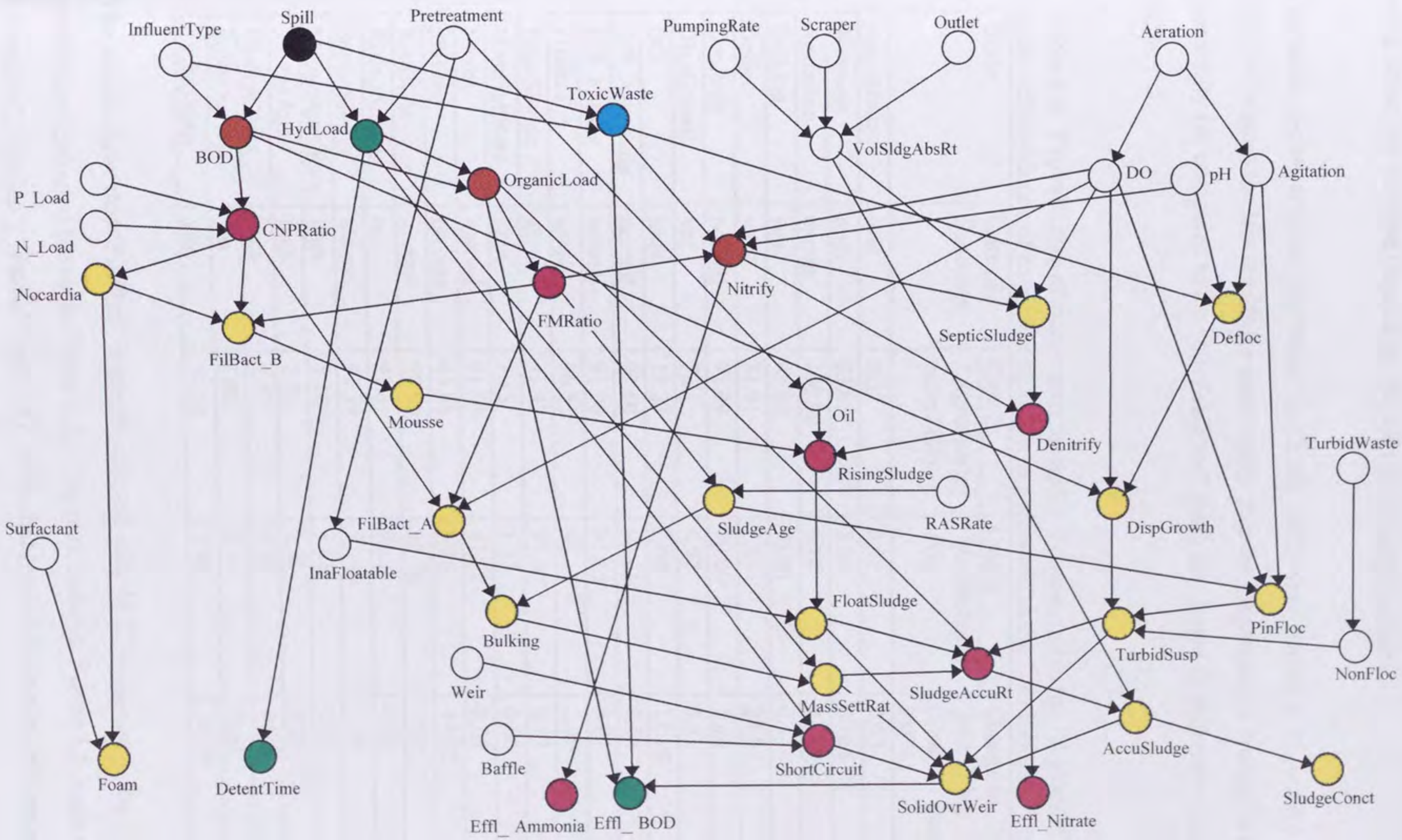

Figure 6.3 The colour of each node *d-connected* to "Spill" indicates the magnitude of change in probability (Case 1).

Case 2: "Agitation": excessive

This case examined whether excessive agitation of the aerators in the aeration basin could cause any adverse impacts on the activated sludge system.

The nodes *d-connected* to "Agitation" in CLAR_NET were shaded in Figure 6.4. Table 6.4 shows the test results for these nodes, and the magnitude of change in node probability (as compared to the "No Evidence" case) are shown in different colours in Figure 6.5.

Table 6.4 Probabilities of occurrence for nodes *d-connected* to the "Agitation" node with evidence of excessive agitation as compared to the "No Evidence" case

Node	State of Condition	Case 2 "Agitation": excess (%)	Case 9 "No Evidence" (%)	Change in probability (Case 2 - Case 9) (%)
AccuSludge	low	0.02	0.02	0.00
Aeration	high	22.65	2.00	20.65
Agitation	**excess**	**100.00**	**6.18**	**93.82**
Bulking	yes	93.92	93.81	0.11
Defloc	yes	31.91	3.84	28.07
Denitrify	normal	91.09	90.06	1.03
DispGrowth	yes	7.31	6.90	0.41
DO	high	13.23	2.08	11.15
Effl_Ammonia	normal	92.60	92.06	0.54
Effl_Nitrate	normal	91.96	91.15	0.81
FilBact_A	absent	96.51	96.11	0.40
FloatSludge	absent	91.37	91.05	0.32
MassSettRate	high	1.15	1.15	0.00
Nitrify	normal	91.91	91.22	0.69
PinFloc	present	45.98	5.16	40.82
RASRate	normal	95.00	95.00	0.00
RisingSludge	no	91.61	91.11	0.50
SepticSludge	absent	92.59	91.40	1.19
SludgeAccuRate	high	5.10	4.95	0.15
SludgeAge	high	2.78	2.78	0.00
SludgeConct	high	9.37	9.35	0.02
SolidOvrWeir	yes	5.88	5.19	0.69
TurbidSusp	yes	34.24	7.80	26.44

The results show that "PinFloc" is greatly affected with 40.82% change in the probability (coloured brown in Figure 6.5). The pink nodes in Figure 6.5, such as "Aeration", "Defloc", "Turbid" and "DO" have changes in probability of between 10 and 30%. The impacts on other nodes are less as expected.

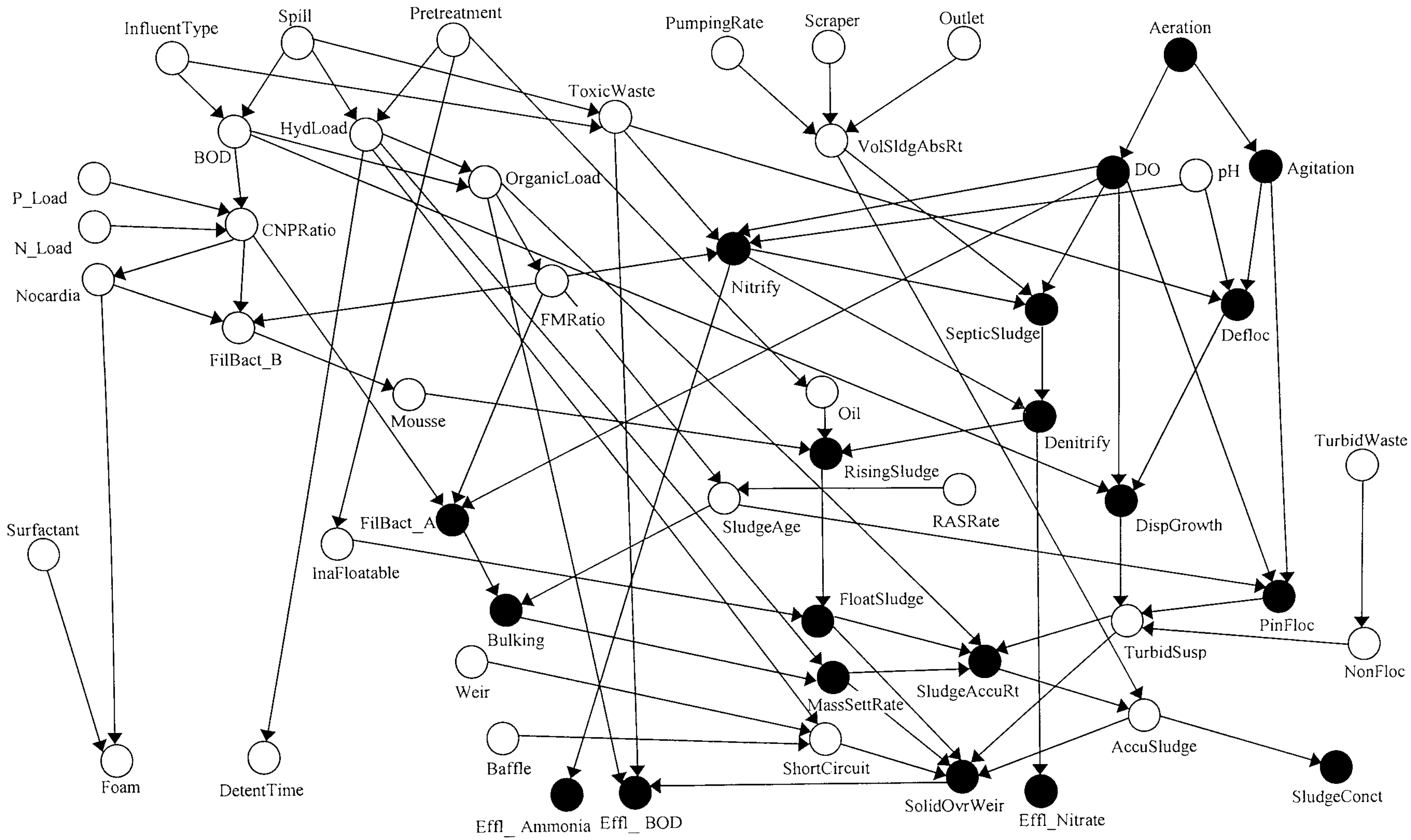

Figure 6.4 Node *d-connected* to "Agitation" node are shaded (Case 2).

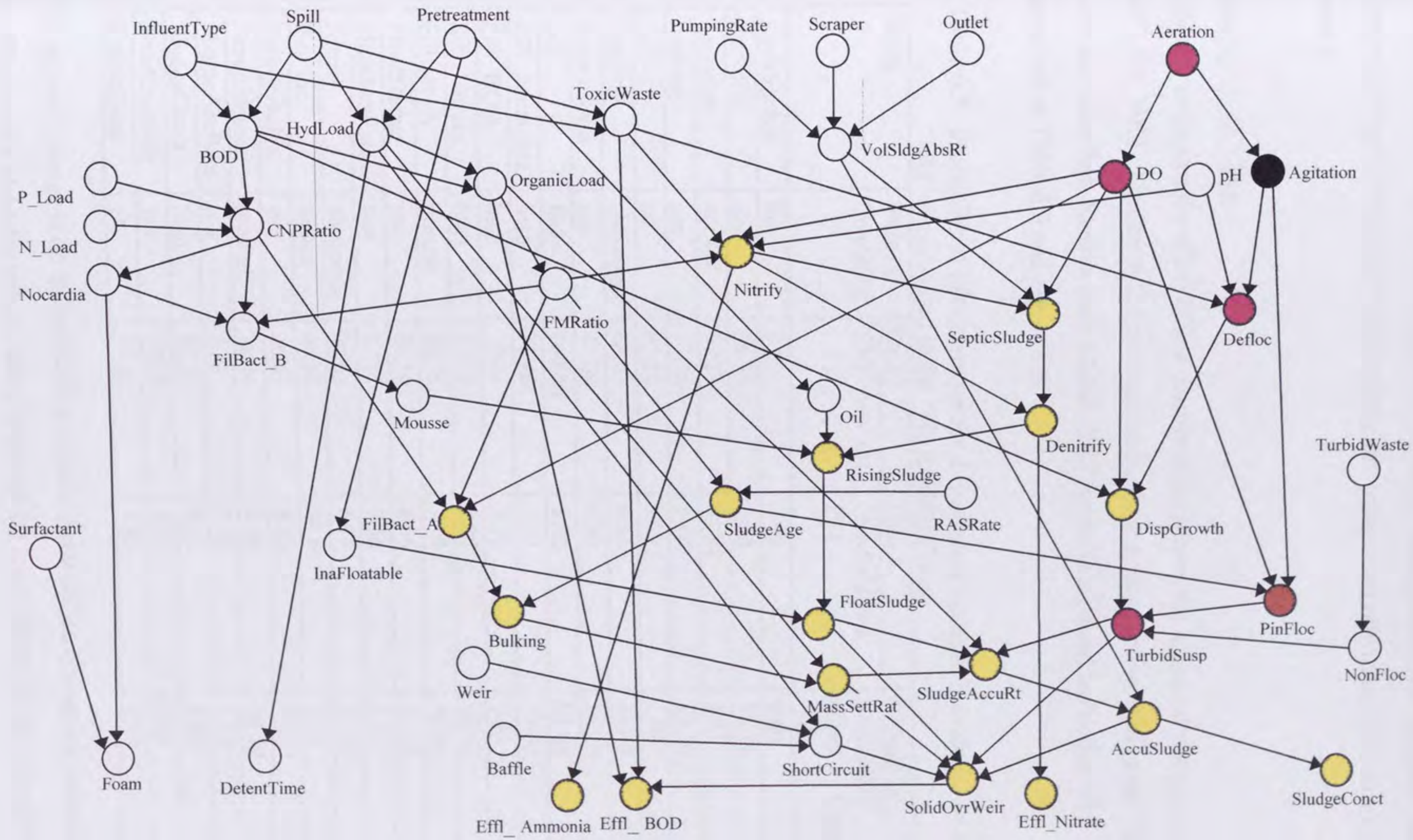

Figure 6.5 Node *d-connected* to “Agitation” are colour-coded to indicate the magnitude of impact due to excess agitation (Case 2).

Thus, the results show that evidence of excessive agitation has major effects on the beliefs in closely related nodes, such as "Aeration" rate, presence of "PinFloc" and "Deflocculation", with the remaining structure being relatively insensitive to such an impact.

Case 3: "DO": low

This test examines the effect of low dissolved oxygen on the activated sludge system in CLAR_NET. Similar to the previous cases, those nodes *d-connected* to the "DO" node are identified. Results from CLAR_NET for these *d-connected* nodes are presented in Table 6.5 and Figure 6.6.

Table 6.5 Probabilities of occurrence for d-*connected* nodeswith evidence of low "DO" as compared to the "No Evidence" case

Node	State of Condition	Case 3 "DO": low (%)	Case 9 "No Evidence" (%)	Change in probability (Case 3 - Case 9) (%)
AccuSludge	low	2.09	2.09	0.04
Aeration	low	66.78	3.00	63.78
Agitation	normal	97.23	93.82	3.41
Bulking	yes	18.35	6.19	12.16
Defloc	no	97.18	96.17	1.03
Denitrify	abnormal	46.42	9.94	36.48
DispGrowth	yes	41.08	6.90	34.18
DO	**low**	**100.00**	**2.92**	**97.08**
Effl_Ammonia	high	20.46	7.94	12.52
Effl_BOD	high	10.41	9.78	0.63
Effl_Nitrate	high	37.73	8.85	28.88
FilBact_A	present	50.76	3.90	46.86
FloatSludge	yes	20.19	8.96	11.23
MassSettRate	low	8.37	3.66	4.71
Nitrify	abnormal	24.63	8.79	15.84
PinFloc	absent	96.98	94.84	2.14
RisingSludge	yes	26.52	8.89	17.63
SepticSludge	present	56.74	8.60	48.14
SludgeAccRate	low	5.32	3.98	1.34
SludgeConct	high	12.73	9.35	0.00
SolidOvrWeir	yes	10.78	5.19	0.99
TurbidSusp	yes	17.66	7.80	9.86

The greatest change is on the probability of low "Aeration" (a change of probability of 63.78%) which correctly reflects that it is one of the main causes of low dissolved oxygen in the actual activated sludge system. The other impacts due to low "DO" are

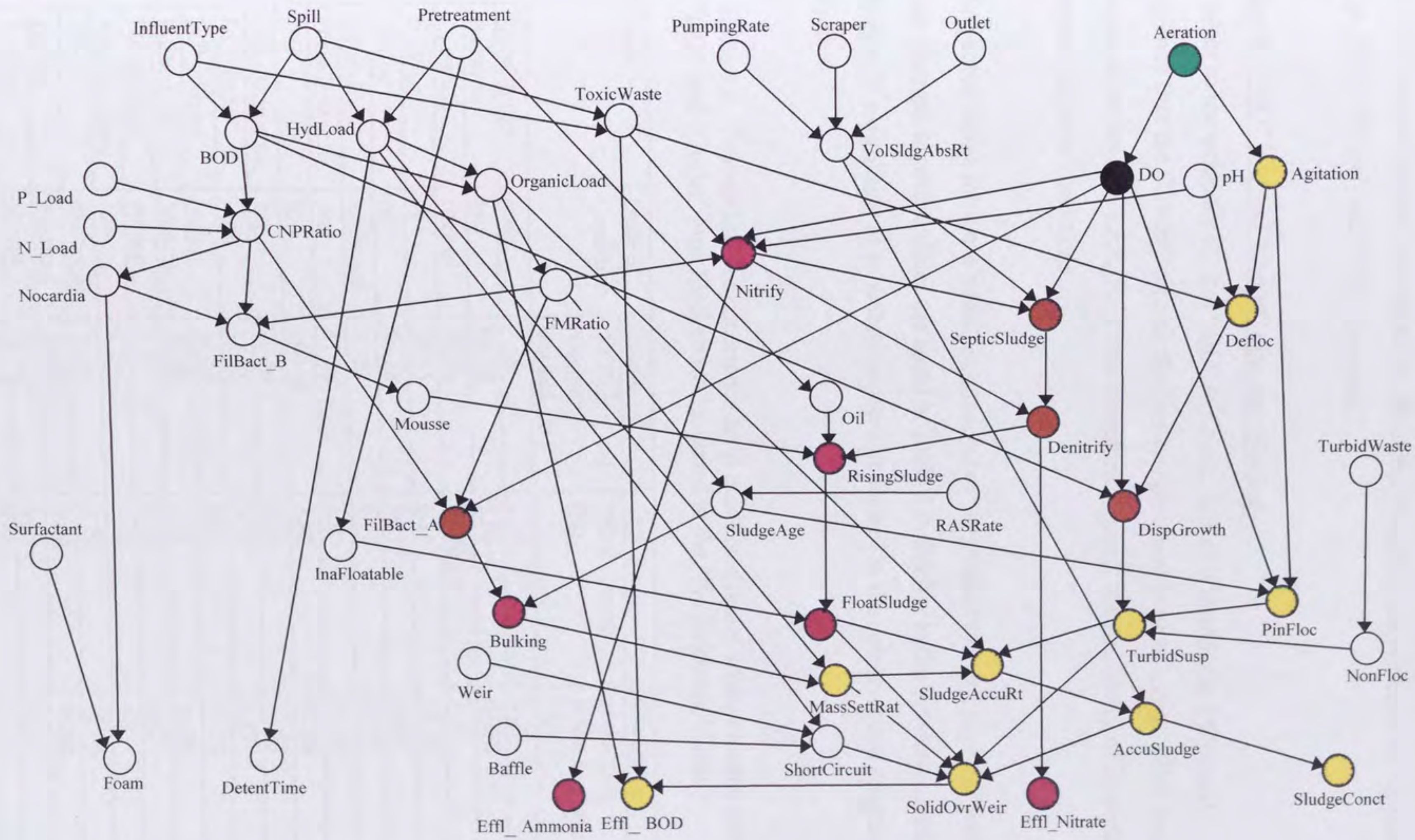

Figure 6.6 Node *d-connected* to "DO" are colour-coded to indicate the magnitude of impact due to low dissolved oxygen (Case 3).

registered for the presence of "SepticSludge", "FilBact_A", "DispGrowth" and "Denitrify" (between 30-50% change in probability shown in brown). Lesser effects (10-30% shown in pink) are noted for abnormal "Nitrify", the presence of "Bulking", high "Effl_Nitrate" and "Effl_Ammonia".

Case 4: "DO" low and "Outlet" pipe was blocked.

Further to the evidence of low "DO" in Case 3, this case introduces additional evidence that the "Outlet" pipe of clarifier was observed to be blocked. With these 2 pieces of evidence, CLAR_NET was examined to check the sensitivity of its nodes in respond to these conditions.

The probabilities for those nodes *d-connected* to "DO" and "Outlet", together with their changes in probabilities are listed in Table 6.6. Similar to the previous cases, the changes in magnitude of probabilities were illustrated in the colour-coded diagram of Figure 6.7.

Table 6.6 Probabilities of occurrence for d-*connected* nodes with evidence of low "DO" and "Outlet" pipe blocked as Compared to the "No Evidence" Case

Node	State of Condition	Case 4 "DO": low and "Outlet": blocked (%)	Case 9 "No Evidence" (%)	Change in probability (Case 4 - Case 9) (%)
AccuSludge	low	7.66	2.10	5.56
Aeration	low	66.78	3.00	63.78
Agitation	normal	97.23	93.82	3.41
Bulking	yes	18.35	6.19	12.16
Defloc	no	97.18	96.17	1.01
Denitrify	abnormal	57.07	9.94	47.13
DispGrowth	yes	41.08	6.90	34.18
DO	**low**	**100.00**	**2.92**	**97.08**
Effl_Ammonia	high	20.46	7.94	12.52
Effl_BOD	high	11.65	9.78	1.87
Effl_Nitrate	high	46.10	8.85	37.25
FilBact_A	present	50.76	3.90	46.86
FloatSludge	present	0.24	0.04	0.02
MassSettRate	low	8.37	3.66	4.71
Nitrify	abnormal	24.63	8.79	15.84
Outlet	**blocked**	**100.00**	**5.00**	**95.00**
PinFloc	absent	96.98	94.84	2.12
RisingSludge	yes	31.67	8.89	22.78
SepticSludge	present	73.00	8.60	64.41

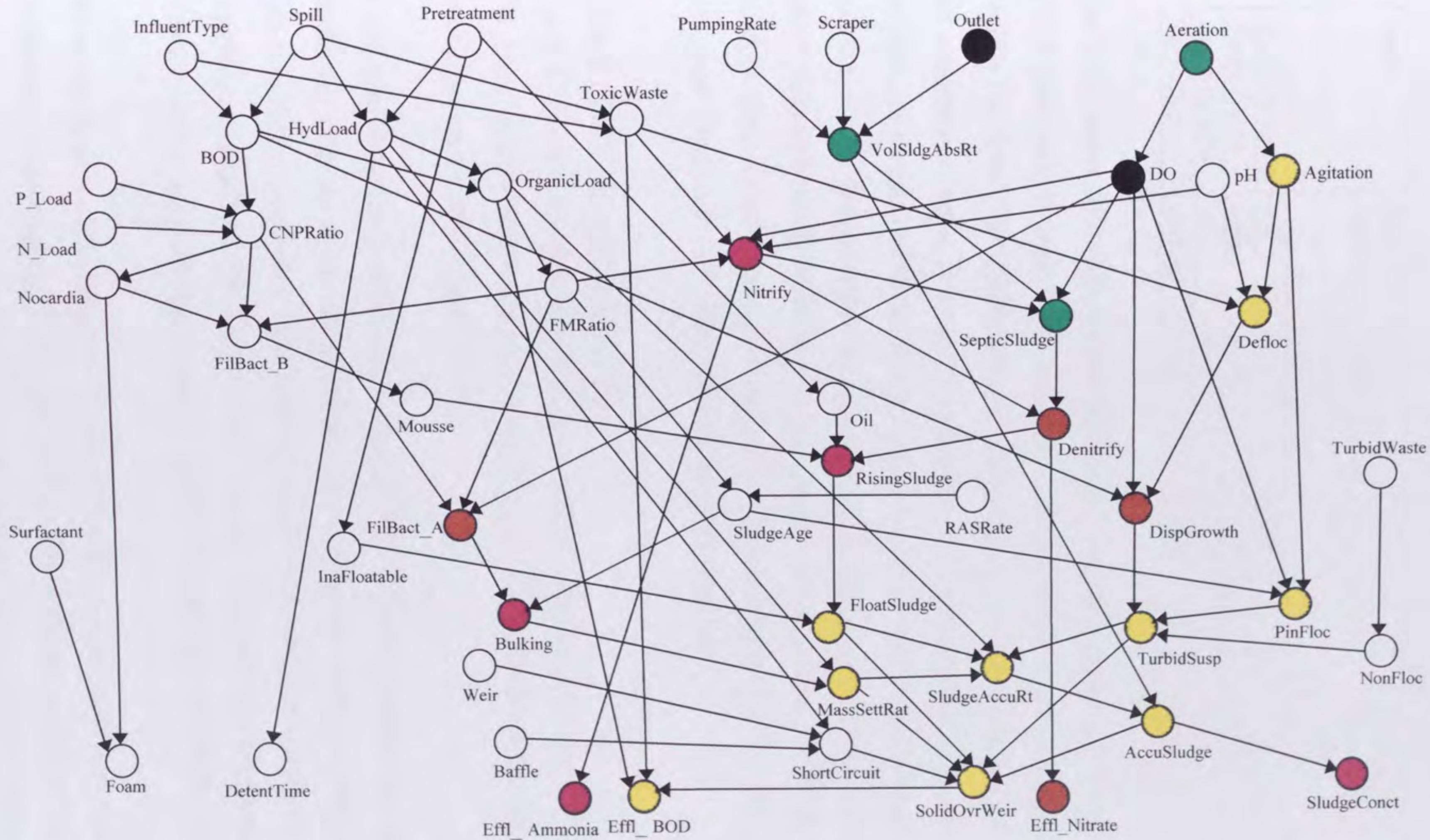

Figure 6.7 Node *d-connected* to "DO" and "Outlet" are colour-coded to indicate the magnitude of impact due to low dissolved oxygen and outlet pipe is blocked (Case 4).

Table 6.6 (Continued) Probabilities of occurrence for d-*connected* nodes with evidence of low "DO" and "Outlet" pipe blocked as Compared to the "No Evidence" Case.

Node	State of Condition	Case 4	Case 9	Change in
		"DO": low and "Outlet": blocked (%)	"No Evidence" (%)	probability (Case 4 - Case 9) (%)
SludgeAccRate	low	5.29	3.98	1.31
SludgeConct	high	32.08	9.35	22.73
SolidOvrWeir	yes	8.13	5.19	2.94
TurbidSusp	present	0.18	0.08	0.10

One of the major differences between the results of this case and those of Case 3 ("DO":low) is the increase in the probability of the occurrence of septic sludge from 56.74% (for Case 3) to 73.00% (Case 4). This is in accordance with expectations of the occurrence of septic sludge under such conditions, which can lead to serious problems in an activated sludge system, requiring immediate corrective actions. In addition, Case 3 does not affect the node probability of low volume sludge abstraction rate ("VolSldgAbsRt"); however, when it is known that the "Outlet" pipe (Case 4) is blocked, there is a substantial increase in the probability from 6.76% (for 'No Evidence' Case) to 65.97% (for Case 4) as would be expected.

Case 5: "DO": low and "N_Load": low.

Table 6.7 gives the probabilities of all nodes that are *d-connected* to "DO" and "N_Load" when evidence is presented that DO is low and N_Load is high. Figure 6.8 shows the same results in graphical form.

Comparing these results with those of Case 3 ("DO": low), it is apparent that the additional evidence of low nitrogen loading in the nutrient feed does not have much effect on the probabilities of those nodes closely *d-connected* to "DO" node, such as the "SepticSludge" (56.76% for both Cases 3 and 5), "Aeration" (66.78% for both Cases 3 and 5), and abnormal "Denitrify" (46.42% for Case 3 to 46.44% for Case 5).

However, those *d-connected* nodes close to "N_Load" show increases in probability, mainly due to the evidence of "N_Load", and less due to the impact of low "DO". For example, the probability of high "CNPRatio" increases from 5.82% ("No Evidence" case) to 60.86% (Case 5), the probability of the presence of filamentous bacteria which would not cause bulking ("FilBact_B") increases from 6.40% to 11.39%, and the presence of "Norcardia" shows an increase in probability from 8.85% to 13.64%.

This test case shows that the introduction of a new evidence will impact on the appropriate nodes, whereas those not related will not be affected. This shows the stability of the structure of CLAR_NET in handling irrelevant evidence. This agreed well with the general thinking process of human experts whereby irrelevant evidence does not contribute to the belief of occurrence.

Table 6.7 Probabilities of occurrence for *d-connected* nodes with evidence of low "DO" and low "N_Load" as compared to the "No Evidence" case

Node	State of Condition	Case 5 "DO": low and "N_Load":low (%)	Case 9 "No Evidence" (%)	Change in probability (Case 5 - Case 9) (%)
AccuSludge	low	2.09	2.09	0.00
Aeration	low	66.78	3.00	63.78
Agitation	normal	97.23	93.82	3.41
Bulking	yes	21.17	6.19	14.98
CNPRatio	high	60.86	5.82	55.04
Defloc	yes	27.90	3.84	24.06
Denitrify	abnormal	46.44	9.94	36.50
DispGrowth	yes	41.07	6.90	34.17
DO	**low**	**100.00**	**2.92**	**97.08**
Effl_Ammonia	high	20.49	7.94	12.55
Effl_BOD	high	10.19	9.78	0.41
Effl_Nitrate	high	37.69	8.85	28.84
FilBact_A	present	61.90	3.90	58.00
FilBact_B	present	11.39	6.40	4.99
FloatSludge	present	20.72	9.07	11.65
Foam	excess	13.61	6.36	7.25
MassSettRate	low	9.40	3.66	5.74
Mousse	yes	8.29	5.09	3.20
N_Load	**low**	**100.00**	**3.00**	**97.00**
Nitrify	abnormal	24.68	8.79	15.89
Nocardia	present	13.64	8.85	4.79
PinFloc	absent	96.98	94.84	2.14
RisingSludge	present	27.37	9.06	18.31
SepticSludge	present	56.76	8.60	48.16
SludgeAccRate	low	5.51	3.98	1.53
SludgeConct	high	9.35	9.35	0.00
SolidOvrWeir	yes	6.28	5.19	1.09
TurbidSusp	present	17.61	7.80	9.81

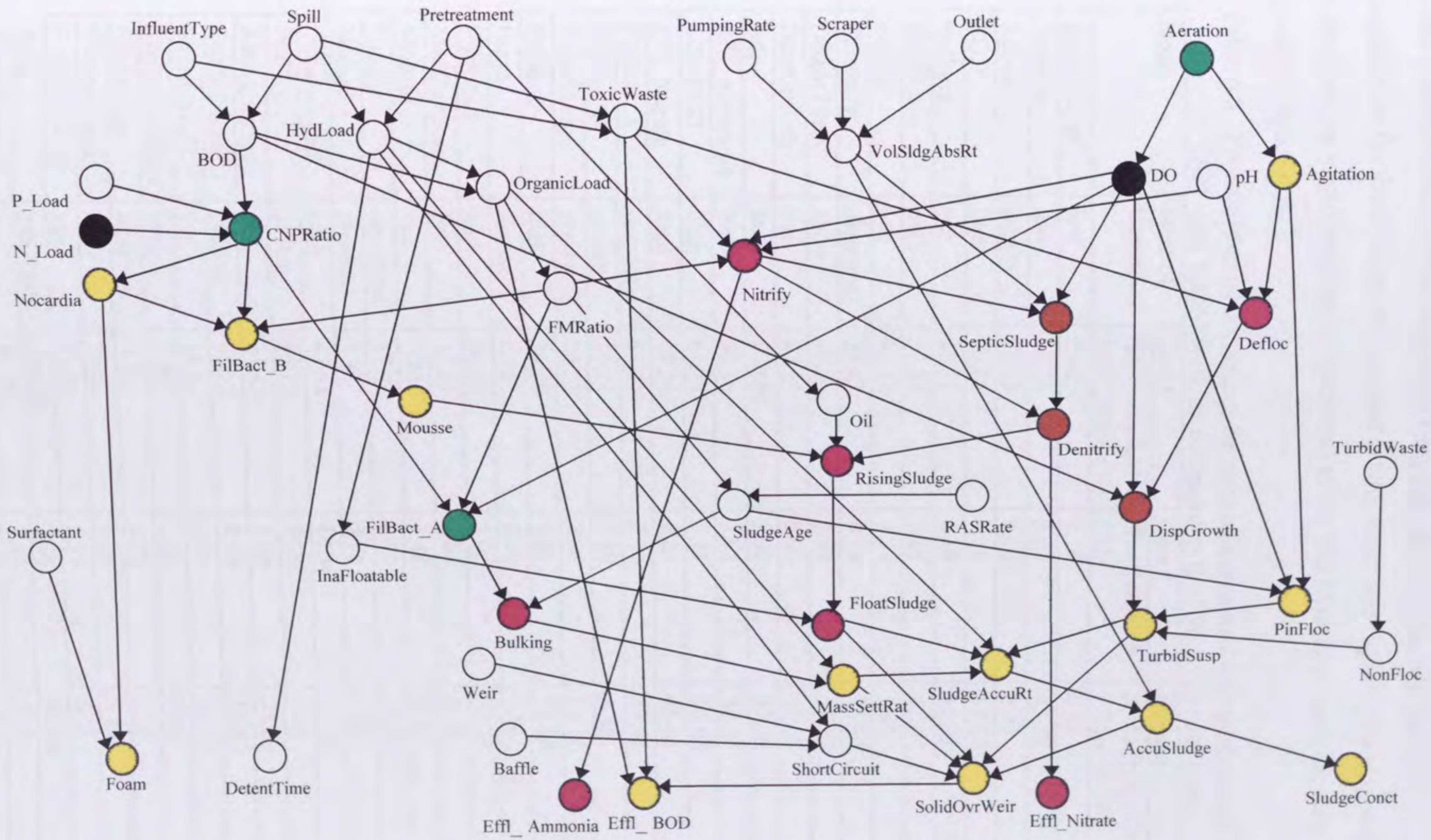

Figure 6.8 Node *d-connected* to "DO" and "N_Load" are colour-coded to indicate the magnitude of impact due to low dissolved oxygen and low Nitrogen loading (Case 5).

Case 6: "DO" low and "Spill" occurs and toxic.

This test case should further demonstrate the impacts of these two pieces of evidence on the other variables in the wastewater treatment plant. Table 6.8 lists the probabilities for those nodes *d-connected* to both "DO" and "Spill". The magnitudes of the changes in probabilities (as compared to the "No Evidence" case) are also shown in Figure 6.9.

Table 6.8 Probabilities of occurrence for nodes *d-connected* with evidence of low "DO" and toxic "Spill" as compared to the "No Evidence" case

Node	State of Condition	Case 6 "DO": low and "Spill":toxic (%)	Case 9 "No Evidence" (%)	Change in probability (Case 6 - Case 9) (%)
AccuSludge	low	2.44	2.10	0.34
Aeration	low	66.78	3.00	63.78
Agitation	excess	97.23	93.82	3.41
BOD	high	53.25	5.15	48.10
Bulking	yes	20.57	6.19	14.38
CNPRatio	high	30.84	5.82	25.02
Defloc	yes	11.12	3.84	7.28
Denitrify	abnormal	38.87	9.94	28.93
DetentTime	short	59.80	5.99	53.81
DispGrowth	yes	47.55	6.90	40.65
DO	**low**	**100.00**	**2.92**	**97.08**
Effl_Ammonia	high	50.36	7.94	42.42
Effl_BOD	high	61.58	5.15	56.43
Effl_Nitrate	high	49.29	8.85	40.44
FilBact_A	present	61.02	3.90	57.12
FilBact_B	present	10.74	3.88	6.86
FloatSludge	present	25.22	8.96	16.26
FMRatio	high	26.10	4.02	22.08
Foam	excess	8.30	6.36	1.94
HydLoad	high	66.00	5.98	60.02
MassSettRate	low	12.38	3.66	8.72
Mousse	yes	7.88	3.48	4.40
Nitrify	abnormal	37.52	8.79	28.73
Nocardia	present	9.85	3.95	5.90
OrganicLoad	high	42.54	10.36	32.18
PinFloc	absent	96.12	94.84	1.28
RisingSludge	yes	34.42	8.89	25.53
SepticSludge	present	64.12	8.60	55.52
ShortCircuit	yes	16.14	4.97	11.17
SludgeAccRate	low	3.98	3.98	0.00
SludgeAge	high	4.73	2.78	1.95
SludgeConct	high	11.52	9.35	2.17
SolidOvrWeir	yes	11.90	5.19	6.71
Spill	**yes_toxic**	**100.00**	**2.50**	**97.50**
ToxicWaste	yes	86.50	5.49	81.01
TurbidSusp	yes	20.20	7.80	12.40

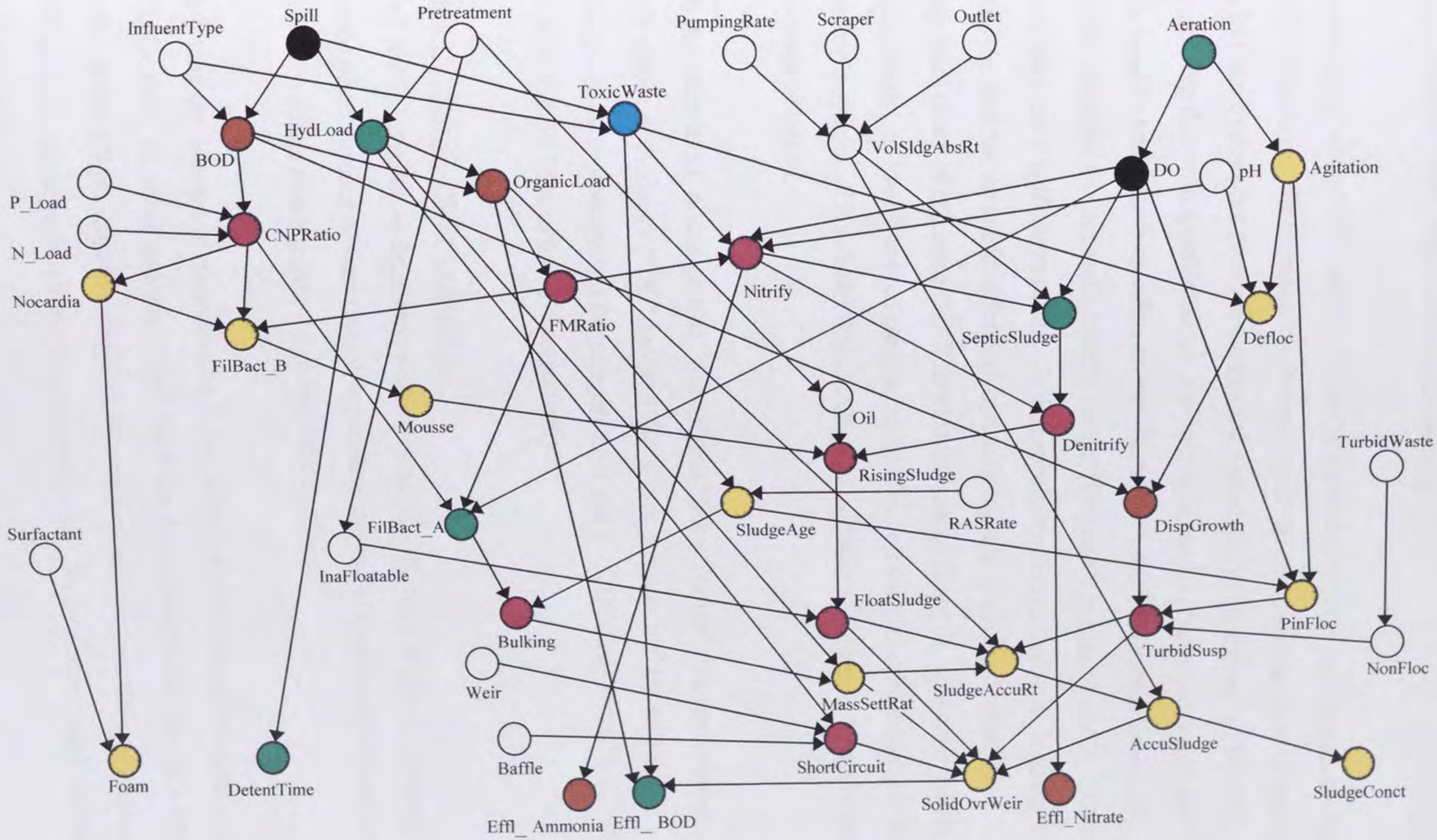

Figure 6.9 Node *d-connected* to "DO" and "Spill" are colour-coded to indicate the magnitude of impact due to low dissolved oxygen and toxic spill (Case 6).

Similar to the previous case (Case 5), the results indicate that those nodes *closely d-connected* to the evidence nodes exhibit the largest increases in probability, with no effect on those nodes which are not *d-connected.*

For example, when "DO" was low (Case 3), the probability of low "Aeration" was 66.78%; however, the introduction of toxic "Spill" as an additional piece of evidence (as in Case 6) does not increase the existing probability of "Aeration" of 66.78%. Comparing this with a real situation, the prediction can be considered sound because a spill would clearly have no effect on the "Aeration" rate. To illustrate this point further, consider the hydraulic loading node ("HydLoad") in cases 1 and 3. In the event only toxic spill occurs (Case 1), the probability of high hydraulic loading is 66.01%; and the same result for high hydraulic loading is obtained when an additional piece of evidence ("DO":low) is introduced (Case 6). It is clear that in actual situation, low dissolved oxygen has no effect on the hydraulic loading of the treatment system. This shows that CLAR_NET is stable with respect to irrelevant evidence obtained.

On the other hand, nodes such as "Nitrify" and "SepticSludge" that are *d-connected* to both pieces of evidence ("DO":low and "Spill":yes_toxic as in this case) show changes in their probabilities (as compared to Case 3: "DO": low) from 24.63% to 37.52% and 56.75% to 64.12% respectively.

<u>Case 7: "SolidOvrWeir": excessive.</u>

This test is intended to determine whether or not CLAR_NET is able to diagnose the causes of occurrence of faults which appeared at the end of treatment process, such as excessive solids flowing over the weirs of the clarifiers.

Applying the concept of *d-connection*, it was identified that with the exception of "Surfactant", all other nodes in CLAR_NET are *d-connected* to the "SolidOvrWeir" node. Table 6.9 presents the whole list of node probabilities; and the magnitudes of change in the node probabilities (as compared to the "No Evidence" case) are shown in Figure 6.10.

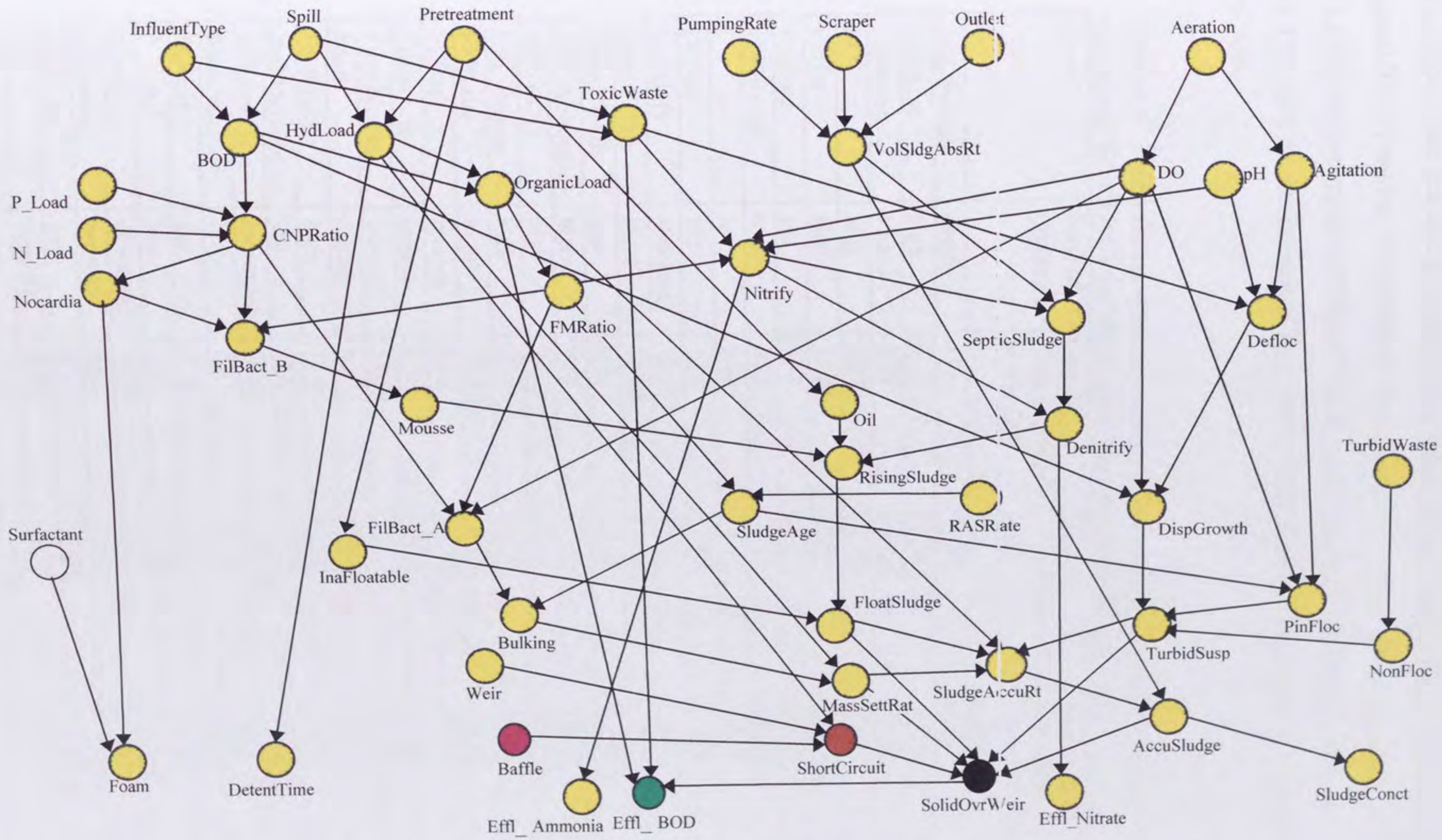

Figure 6.10 Node *d-connected* to "SolidOvrWeir" are colour-coded to indicate the magnitude of impact due to excess solids flowing over the weirs (Case 7).

Table 6.9 shows that with the evidence of "SolidOvrWeir" introduced, the probabilities for all the *d-connected* nodes are changed as compared to the "No Evidence" case, but that for some of them, the change is quite small. For example, the probability of excess "AccuSludge" increases from 5.54% ("No Evidence" case) to 11.53%, the occurrence of "ShortCircuit" in the flow increases from 4.97% to 44.32%, and the occurrence of high "Effl_BOD" shows an increase from 9.77% to 71.79%.

Table 6.9 Probabilities of occurrence for nodes *d-connected* with evidence of excessive "SolidOvrWeir" as compared to the "No Evidence" case

Node	State of Condition	Case 7 "SolidOvrWeir": excess (%)	Case 9 "No Evidence" (%)	Change in probability (Case 7 - Case 9) (%)
AccuSludge	excess	11.53	5.54	5.99
Aeration	high	2.20	2.00	0.20
Agitation	excess	6.99	6.18	0.81
BOD	high	6.97	5.15	1.82
Baffle	faulty	19.84	5.00	14.84
Bulking	yes	9.77	6.19	3.58
CNPRatio	high	6.83	5.82	1.01
DO	low	3.48	2.92	0.56
Defloc	yes	4.38	3.84	0.54
Denitrify	abnormal	12.55	9.94	2.61
DetentTime	short	14.79	5.99	8.80
DispGrowth	yes	8.40	6.90	1.50
Effl_Ammonia	high	9.58	7.94	1.64
Effl_BOD	high	71.79	9.77	62.02
Effl_Nitrate	high	10.91	8.85	2.06
FMRatio	high	10.31	6.52	3.79
FilBact_A	present	4.88	3.90	0.98
FilBact_B	present	4.70	3.88	0.82
FloatSludge	present	14.59	9.07	5.52
Foam	excess	6.37	6.36	0.01
HydLoad	high	15.84	5.98	9.86
InaFloatable	yes	11.07	8.00	3.07
InfluentType	industrial	55.00	55.00	0.00
MassSettRate	low	9.63	3.66	5.97
Mousse	yes	4.10	3.48	0.62
N_Load	low	3.00	3.00	0.00
Nitrify	abnormal	10.86	8.79	2.07
Nocardia	present	3.96	3.95	0.01
NonFloc	yes	9.15	8.00	1.15
Oil	present	8.80	8.75	0.05
OrganicLoad	high	16.57	10.36	6.21

Table 6.9 (Continued) Probabilities of occurrence for nodes *d-connected* with evidence of excessive "SolidOvrWeir" as compared to the "No Evidence" case

Node	State of Condition	Case 7 "SolidOvrWeir": excess (%)	Case 9 "No Evidence" (%)	Change in probability (Case 7 - Case 9) (%)
Outlet	blocked	6.77	5.00	1.77
P_Load	high	2.01	2.00	0.01
PinFloc	present	6.91	5.16	1.75
Pretreatment	poor	8.70	5.00	3.70
PumpingRate	low	4.10	4.00	0.10
RASRate	low	4.14	4.00	0.14
RisingSludge	yes	12.99	8.89	4.10
Scraper	abnormal	6.56	5.00	1.56
SepticSludge	present	10.45	8.60	1.85
ShortCircuit	yes	44.32	4.97	39.35
SludgeAccRate	low	4.88	3.98	0.90
SludgeAge	low	2.81	2.76	0.05
SludgeConct	high	14.10	9.35	4.75
SolidOvrWeir	**excess**	**100.00**	**5.19**	**94.81**
Spill	yes_toxic	5.19	2.50	2.69
ToxicWaste	yes	8.04	5.49	2.55
TurbidSusp	yes	11.75	7.80	3.95
TurbidWaste	present	5.19	5.00	0.19
VolSldgAbsRt	low	10.48	6.77	3.71
Weir	not_level	12.28	5.00	7.28
pH	abnormal	5.05	5.00	0.05

Even for nodes that are many "generations" away from the "SolidOvrWeir" node such as "Scraper" shows an increase in probability of faulty behaviour occurrence from 5.00% (for "No Evidence" case) to 6.56%. The small increase in probabilities for some of the nodes showed that further evidence or observation was needed to improve the diagnosis.

Case 8: "SolidOvrWeir": excessive and "ToxicWaste": present.

An additional piece of evidence, the presence of "ToxicWaste" in the mixed liquor of wastewater treatment plant was introduced to the condition in Case 7 ("SolidOvrWeir": excessive). This was intended to further check the sensitivity and stability of CLAR_NET in responding to evidence ("SolidOvrWeir") from the end of treatment process as well as evidence ("ToxicWaste") from the "upstream" end of the treatment process.

The node probabilities for this case and the "No Evidence" are presented in Table 6.10; and the effect of the changes illustrated in Figure 6.11.

Table 6.10 Probabilities of occurrence for nodes *d-connected* with evidence of excessive "SolidOvrWeir" and the presence of "ToxicWaste" as compared to the "No Evidence" case

Node	State of Condition	Case 8 "SolidOvrWier": excess and "ToxicWaste": present (%)	Case 9 "No Evidence" (%)	Change in probability (Case 8 - Case 9) (%)
AccuSludge	excess	12.93	5.54	7.39
Aeration	high	2.17	2.00	0.17
Agitation	excess	6.83	6.18	0.65
BOD	high	31.53	5.15	26.38
Baffle	faulty	14.61	5.00	9.61
Bulking	yes	9.21	6.19	3.02
CNPRatio	high	19.63	5.82	13.81
DO	low	3.34	2.92	0.42
Defloc	yes	14.41	3.84	10.58
Denitrify	abnormal	35.56	9.94	25.62
DetentTime	short	50.69	5.99	44.70
DispGrowth	yes	12.65	6.90	5.75
Effl_Ammonia	high	48.78	7.94	40.84
Effl_BOD	high	93.53	9.77	83.76
Effl_Nitrate	high	29.09	8.85	20.24
FMRatio	high	28.03	6.52	21.51
FilBact_A	present	6.47	3.90	2.57
FilBact_B	present	8.03	3.88	4.15
FloatSludge	present	22.05	9.07	13.09
Foam	normal	93.88	93.64	0.24
HydLoad	high	55.96	5.98	49.98
InaFloatable	yes	9.95	8.00	1.95
InfluentType	industrial	70.48	55.00	15.48
MassSettRate	low	11.13	3.66	7.47
Mousse	yes	6.24	3.48	2.76
N_Load	low	3.02	3.00	0.02
Nitrify	abnormal	60.48	8.79	51.69
Nocardia	absent	96.41	96.05	0.36
NonFloc	yes	8.39	8.00	0.39
Oil	present	10.75	8.75	2.00
OrganicLoad	high	45.98	10.36	35.62
Outlet	blocked	6.14	5.00	1.14
P_Load	high	2.01	2.00	0.01
PinFloc	present	7.46	5.16	2.30
Pretreatment	poor	7.20	5.00	2.20
PumpingRate	low	4.28	4.00	0.28
RASRate	low	4.12	4.00	0.12

Table 6.10 (Continued) Probabilities of occurrence for nodes d-*connected* with evidence of excessive "SolidOvrWeir" and the presence of "ToxicWaste" as compared to the "No Evidence" case.

Node	State of Condition	Case 8 "SolidOvrWier": excess and "ToxicWaste": present (%)	Case 9 "No Evidence" (%)	Change in probability (Case 8 - Case 9) (%)
RisingSludge	yes	24.79	8.89	15.90
Scraper	abnormal	6.00	5.00	1.00
SepticSludge	present	17.65	8.60	9.05
ShortCircuit	yes	59.37	4.97	54.40
SludgeAccRate	high	18.75	4.95	13.80
SludgeAge	high	5.26	2.77	2.49
SludgeConct	high	15.21	9.35	5.86
SolidOvrWeir	**excess**	**100.00**	**5.19**	**94.81**
Spill	yes_toxic	56.04	2.50	53.54
ToxicWaste	**yes**	**100.00**	**5.49**	**94.51**
TurbidSusp	yes	13.27	7.80	5.47
TurbidWaste	present	5.15	5.00	0.15
VolSldgAbsRt	low	9.17	6.77	2.40
Weir	not_level	10.10	5.00	5.10
pH	abnormal	5.06	5.00	0.06

The additional evidence ("ToxicWaste": high) increases the probability of high effluent BOD ("Effl_BOD") from 71.79% (Case 7) to 93.53% (Case 8) as shown in Table 6.10. It also increases the probability of toxic "Spill" from 5.19% (Case 7) to 56.04% (Case 8) as expected.

However, the new evidence about toxic waste has reduced belief in the baffle being faulty from 19.84% to 14.61%. This is in keeping with expectation in a real situation, and clearly shows that CLAR_NET is able to retract belief when new evidence *explains away* the prior belief that the baffle was faulty. The same applied for the probabilities for other nodes such as faulty "Scraper" and unlevelled "Weir" which have the probabilities reduced from 6.56% to 6.00% and 12.28% to 10.10% respectively.

Case 9: "No Evidence" Case

This test case was used as a "control" case, whose node probabilities served as the base case from which all other cases could be compared. Results for this case are presented in Figure 6.1.

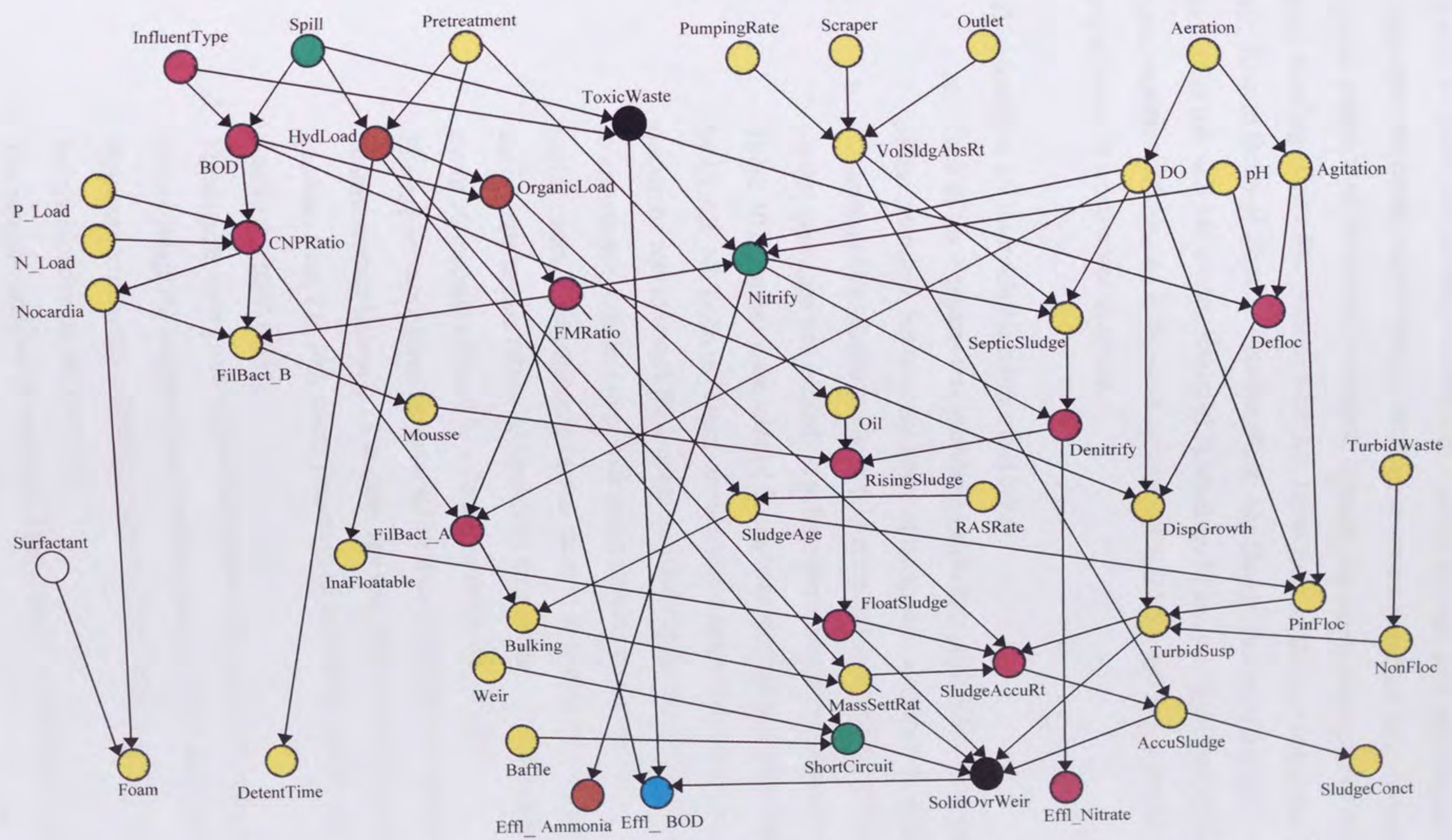

Figure 6.11 Node *d-connected* to "SolidOvrWeir" and "ToxicWaste" are colour-coded to indicate the magnitude of impact due to excess solids flowing over the weirs and the presence of toxicwaste (Case 8).

6.6 Eliciting Opinion of Experts to Assess Network Performance

In order to assess the accuracy of the results from the network, four experienced wastewater treatment supervisors in United States were selected and interviewed. Careful selection of the experts were made to ensure the results obtained will be of good standing. These four persons were: Mr. James Bunn of Du Pont Industries Inc., Mr. Ronald Berry of Hoechst Celanese Plant, Mr. David Centioni of ABCO Industries Inc. and Ms. Nancy Hakim of Spartanburg Municipal Treatment Plants. All these experts were located in the south eastern region of USA and they were very experienced in wastewater treatment.

The procedure for interviews is summarised below.

a. Each of the 4 experts was interviewed separately; all of them were told of the interview, but were not aware of the specific questions to be asked.
b. A questionnaire (shown in Figure 6.14 at the end of this Chapter) with 30 pre-set questions was handed out to the experts during the interview. These 30 questions were selected from a wide range of test cases simulated by CLAR_NET. An important consideration made when setting the questions was to ensure these questions were simple enough for the experts to answer yet sufficient to provide sample checks on the system's performance. This consideration was made so as to gain the cooperation of the experts in case follow-up interviews were needed. The author felt that about 30 questions should be sufficient to meet such criteria.
c. The experts were given the same information for a specific wastewater treatment plant known to all of them, and they were asked to score each question from 1 to 100, where 1 represented the least probable, and 100 was for the most likely.
d. The experts were given ample time to answer the questions. They were free to obtain the response from whatever means possible, such as using their own experience, referring to manuals. They could also ask the author for clarification on any question.
e. The results consisted of the recorded responses from the experts, and these were listed in Table 6.11.

6.7 Comparing the Results from CLAR_NET to the Experts' Opinion

To justify the effectiveness of the belief network, the following exercise was conducted to measure its performance quantitatively against the judgment of domain experts.

The quantitative method of measuring the belief network performance was devised to establish a scientific way of evaluating its degree of success, which is determined by the size of the percentage error.

The procedures, with examples, are described below.

a. Calculate the *Error* for each test case, where:

$$\textit{Error (\%)} = \left| \textit{(Expert's Response - CLAR\_NET Result)} \right| \quad (6.1)$$

The responses from the experts for the 30 test cases (in response to the questionnaire at the end of the chapter) were entered into Table 6.11. Simulated results from CLAR_NET were also entered. The difference in the simulated result and the expert's opinion for each case was entered in the "Error" column, using Eqn. (6.1) above.

For example, in case 1, Expert 1 gave a response of 55% whereas CLAR_NET was 56.80%, thus,
Error = 56.80% - 55.00% = 1.8%

b. From the responses of each expert, calculate the root mean square (RMS) of error (in terms of percentage) to determine the overall systems performance, in which:

$$RMS = \left[\frac{\sum_{N}^{1} E^2}{N} \right]^{0.5} \quad (6.2)$$

and, N = number of cases (N=30 as in this case)
E = Error (percentage) as defined in Eqn. (6.1)

From Table 6.11,

$$\text{RMS of error for case 1} = [(1.8^2 + 1.1^2 + \ldots \ldots + 4.9^2)/4]^{0.5} = 3.65\%$$

c. Calculate the RMS of the RMSs for the four cases.

$$\text{RMS of the RMSs of Error} = [(RMS_1^2 + RMS_2^2 + RMS_3^2 + RMS_4^2)/4]^{0.5} \quad (6.3)$$
$$= 7.37\%$$

where, for instance, RMS_1 = root mean square of error for test case 1.

6.7.1 Analysis of Results

The following observations are noted from Table 6.11, in comparing the results from CLAR_NET and the four domain experts.

a. Most of the results simulated by CLAR_NET are in general agreement with those predicted by the four experts.

b. The biggest error between an expert's opinion and a CLAR_NET result was 22.8% and the lowest was 0%. Consider the range of 0-100% for such assessment, the error is small and acceptable.

c. The root mean square of error (RMS) ranges from 3.65% (Case 1) to a maximum of 8.47% (Case 2), with the RMS of RMSs of Error of 7.37% for the four sets of results evaluated in Table 6.11. This range is considerably small for such a system. This is because in a wastewater treatment process, there is a considerable variation in the operating performance of a biological wastewater treatment, and the different experience of the 4 domain experts also contributed to this slight difference in opinion.

d. Responses from the four domain experts show that human experts tend to have their own way of setting high and low ranges in predicting probabilities. For example, it is evident in Table 6.11 where Experts 2, 3 and 4 tend not to give below 10 for the least likely cases. Experts 1 and 4's upper limit is 95 instead of 100 for Expert 2 and 99 for Expert 3.

In general, it can be concluded that the analysis has been conducted successfully, with good results obtained. This shows that CLAR_NET is able to simulate results within the range close to the expectation of the human experts.

6.8 Summary for Results of Tests Conducted

With the various tests conducted to check the accuracy of simulated results from CLAR_NET, it can be concluded that CLAR_NET is able to diagnose faults and predict the performance of clarifiers and aeration basins within an activated sludge system of a typical wastewater treatment system, as defined earlier.

A summary of the various test results is given below.

1. Under the 'No Evidence" case, that is, when the wastewater treatment process functions well with no evidence of any problem, CLAR_NET gave the probabilities for all the relevant nodes indicating normal operation (for example, "absent" condition for "SepticSludge", etc.) to be at least 90%. This conforms within the expectation of a good treatment system.

2. CLAR_NET has the capability to perform both "predictive" and "diagnostic" of wastewater treatment process as shown in Section 6.4. The results, as compiled in Table 6.2 and transferred to Table 6.11 for comparison with the experts' predictions, were found to be good and well within the expected range of experts' predictions.

3. The eight cases of sensitivity tests conducted showed CLAR_NET was "sensitive" enough to respond to changes in the node probabilities due to a change in the evidence for those nodes that are d-connected. At the same time, the CLAR_NET structure remained stable and was insensitive to any irrelevant evidence obtained. The changes in node probabilities were well within the general expectation of a wastewater treatment plant.

4. However, Section 6.5 should have shown some cases of CLAR_NET in dealing with correlated evidence. In such a situation, multiple and independent sources in the a network would normally increase the credibility of a hypothesis, but the discovery that these sources have a common origin should reduce the credibility. Though Case 8 where "ToxicWaste:present" and "SolidOverWeir: excess" was close to indicate such a situation, other cases such as having evidence in "FilBact_A: present" and "SludgeAge: high" to find out the probabilities of occurrence of "Bulking:present" would reflect well the correlated evidence. This is because both "FilBact_A" and "SludgeAge" nodes originated from the same parent node "FMRatio".

5. Predictions from CLAR_NET were observed to be in a range close to the experts' predictions, as indicated by the small Average RMS of 7.09% in Table 6.11.

Table 6.11 Comparison of CLAR_NET results with experts' responses

Cases	CLAR_NET Results (%)	Expert 1 (%)	Error (%)	Expert 2 (%)	Error (%)	Expert 3 (%)	Error (%)	Expert 4 (%)	Error (%)
1	56.80	55	1.8	50	6.8	45	11.8	50	6.8
2	41.10	40	1.1	55	13.9	50	8.9	40	1.1
3	17.30	15	2.3	20	2.7	15	2.3	40	22.7
4	73.00	80	7	80	7	65	8	70	3
5	12.60	15	2.4	30	17.4	20	7.4	20	7.4
6	61.70	70	8.3	80	18.3	80	18.3	70	8.3
7	39.50	35	4.5	30	9.5	40	0.5	30	9.5
8	87.60	85	2.6	90	2.4	75	12.6	85	2.6
9	93.60	90	3.6	85	8.6	90	3.6	95	1.4
10	47.20	50	2.8	55	7.8	45	2.2	70	22.8
11	10.10	10	0.1	15	4.9	10	0.1	10	0.1
12	61.50	60	1.5	70	8.5	70	8.5	65	3.5
13	93.20	95	1.8	85	8.2	85	8.2	90	3.2
14	82.90	80	2.9	85	2.1	95	12.1	85	2.1
15	91.70	95	3.3	95	3.3	90	1.7	90	1.7
16	70.10	70	0.1	80	9.9	65	5.1	70	0.1
17	45.60	45	0.6	50	4.4	40	5.6	55	9.4
18	90.00	90	0	100	10	99	9	90	0
19	95.60	95	0.6	85	10.6	85	10.6	90	5.6
20	6.80	7.5	0.7	10	3.2	10	3.2	10	3.2
21	71.80	80	8.2	90	18.2	85	13.2	85	13.2
22	12.20	15	2.8	10	2.2	20	7.8	10	2.2
23	91.10	90	1.1	85	6.1	85	6.1	85	6.1
24	94.80	90	4.8	95	0.2	95	0.2	85	9.8
25	10.20	10	0.2	10	0.2	10	0.2	15	4.8
26	82.70	90	7.3	85	2.3	90	7.3	95	12.3
27	92.80	90	2.8	95	2.2	85	7.8	90	2.8
28	45.70	45	0.7	45	0.7	50	4.3	50	4.3
29	62.20	65	2.8	70	7.8	70	7.8	70	7.8
30	55.10	60	4.9	50	5.1	50	5.1	60	4.9
RMS of Error (%) =			3.651758		8.473114		7.949444		8.310255

Average RMS of Error (%) = **7.096143**

Note:
1. Error (for each case) = ABS(Expert's Opinion - Network's Results)
2. Root Mean Square (RMS) of Error = SQRT[{SQ(Error1)+SQ(Error2)+...SQ(Error30)}/30]
3. Average Root Mean Square of Error =(RMS of Error 1 + RMS of Error 2...+RMS of Error 4)/4

CHAPTER 7 CONCLUSION

7.1 Summary of Work Completed

The work described in this thesis was largely motivated by a desire to find a suitable computing tool to emulate human experts in diagnosing faults in wastewater treatment system. Due to the highly dynamic nature of wastewater treatment processes, rapid and reliable diagnosis of faults is essential so that immediate actions can be taken before the problems escalate. This objective has been achieved by the application of Bayesian Belief Networks to develop a prototype network known as CLAR_NET. Through numerous refinements and tests, CLAR_NET has demonstrated that it is capable of predicting faults in the activated sludge system of a wastewater treatment process to an accepted degree of accuracy and in fair agreement with the opinion of human experts.

In the early development stage of the system, a rule-based approach to expert systems was selected due to its computational convenience. As a result, a prototype system known as CLAR_EX was developed. However, CLAR_EX was not able to handle uncertainty in a suitable way due to its inability to handle bi-directional reasoning dynamically.

In wastewater treatment system, the processes involved are complex and the behaviour is usually uncertain. As such, bi-directional reasoning is needed in diagnosing its faults or predict its effects. The updating algorithm inherent in the Bayesian Belief Networks makes the method a more appropriate choice than the rule-based expert system. Consequently, CLAR_NET was developed to replace CLAR_EX and has proved to effectively predict and diagnose faults in the activated sludge system.

In general, the CLAR_NET developed possesses the following characteristics and uses:

- it is a prototype representing a complex subsystem of a typical wastewater treatment system - a full system is not feasible to be developed here because this would need substantially more resources, especially in terms of time and skilled manpower.
- it has clearly demonstrated the potential values of Bayesian Belief Network in wastewater treatment operation - such as the ability to handle uncertainties,
- it has proved, through various tests conducted, to produce results that are in general agreement with experts' opinion,
- it can be easily adapted as a training tool for new wastewater treatment operators to learn about the wastewater treatment and for the advanced operators to sharpen their judgement in troubleshooting and remedial actions.

The following sections will also discuss and summarize the reasons for adopting BBNs and the lessons learned through the research, so that future research and development work in this area can be identified.

7.2 The Choice of BBN's versus Rule-Based Systems

When human experts carry out diagnosis of any faults that occur, they usually reason in their minds bi-directionally by evaluating the causes and effects, and weigh the uncertainties involved. They often do so using some kind of mental model based on their knowledge and experience, probably without realising it themselves. Their existing prior beliefs may change when they know more about the circumstances, or when new evidence is received. Thus, any computer system designed to emulate human experts must possess a bi-directional reasoning facility and a mathematically sound method of updating beliefs.

The classical logic method, which reasons uni-directionally and assumes that all relationships are exact, is therefore not a suitable model. This method, however, forms the basis for the rule-based expert systems approach to reasoning. For example, given a condition "If A then B", an exact relationship is assumed here, which simply means that if A is found anywhere in the database, then B is certainly true regardless of how A was derived ("detachment") and regardless of all other data in the database ("locality"). It cannot be concluded from the above rule that the condition "If B then A" is also true. So long as detachment and locality are satisfied, the system can be made modular, which enables relative ease in computation.

However, diagnosis of faults in most system, such as a wastewater treatment system, requires *plausible reasoning*, which deals with relationships that are inherently uncertain and inexact. This means that the classical logic method cannot be used here, since detachment and locality cannot be assumed. Plausible reasoning requires dynamic bi-directional reasoning, which should predict from A to B, and in turn can diagnose from B back to A. Only in this way can an initial belief be retracted when new evidence *explains away* earlier evidence. In addition, it requires all evidence to be considered, not just A, when predicting a conclusion about B from A, unless the evidence is irrelevant to B (that is, d-separated).

The rule-based expert systems approach to plausible reasoning is based on classical logic, and handles the uncertainty in the relationships through an *ad hoc* probabilistic calculus based on certainty factors. Though the modular structure of the rule-based approach enables computational efficiency, it can result in serious inconsistent and erroneous conclusions. Chapter 3 of this thesis has provided illustrations with examples on this point. The reason being: there are inadequacies in the *ad hoc* calculus; the assumption of detachment and locality still apply without proving the irrelevance; the inability of the method to reason bi-directionally and the inability to handle correlated evidence in a mathematically sound way. The inadequacies inherent in this method, led to the abandonment of the development of CLAR_EX, a rule-based expert system initially aimed at diagnosing faults in clarifiers.

Bayesian Belief Networks, on the other hand, through the development of CLAR_NET, demonstrated that they possess all the qualities desired for plausible reasoning and can be used for such diagnostic and predictive tasks.

7.3 Lessons Learned and Future Work

The research work completed here involved a number of stages of development, and these can be broadly summarized as:

a. reviewing published literature,

b. constructing influence diagrams to diagnose faults in wastewater treatment systems and developing a rule-based expert system, CLAR_EX,

c. changing the rule-based expert system into Bayesian Belief Network by constructing the CLAR_NET structure;

d. eliciting knowledge from domain experts in ensuring the validity of the CLAR_NET structure,

e. incorporating prior and conditional probabilities in all the nodes in CLAR_NET to develop the facility to reason uncertainty, and

f. conduct various tests to check the validity of CLAR_NET to conform with human experts' normal range of prediction, and to check the sensitivity and ensure stability of CLAR_NET in dealing with evidence received.

However, these play a part in the research work which are worthwhile to mention here for future refinement of work in this area. Firstly, it was interesting to observe through literature review that, an increasing number of recently published work in the area of expert systems and artificial intelligence (such as Krause and Clark [1993] and Jensen [1996]) mentioned the concept of Bayesian Belief Network, and its superiority over rule-based expert system in handling uncertainty. This justifies the decision made in the mid-stream of the research work to move from rule-based expert system to a Bayesian Belief Network for handling diagnosis in wastewater treatment.

In the early development of the CLAR_EX expert system, inference diagrams were developed in linking the causes to a particular symptom observed in a wastewater treatment system, for ease in transferring into the computer codes in the rule-based system. However, knowledge obtained through literature review indicated that in a wastewater treatment operation, it was not easy to identify all exact causes to a symptom observed because there are many possible configurations in the components of wastewater treatment system. As such, it was decided that the inference diagrams be drawn based on a an activated sludge system of a typical wastewater treatment operation commonly used.

The reason to change from rule-based expert system development to the BBNs was mainly due to the inability of the former in handling uncertainty, this has been discussed earlier. However, there were a number of difficulties encountered during the development of the CLAR_NET Bayesian network. First of all, it was not easy to combine all the 21 inference diagrams into a single network with links showing the causal relationship between the nodes. This was largely overcome by drawing each inference diagram into a belief network before combining them into a single BBNs. However, since wastewater treatment is a dynamic process whereby sometimes there is a viscous circle between "symptoms" and "causes" (for example, low "DO" can cause septic sludge, but it can be argued that septic sludge could cause "DO" to be low), decisions were made based on advise from domain experts to determine which node should be "parent" and which should be "child". Fortunately, the ability of BBNs to handle bi-directional reasoning has lessened the burden in structuring the CLAR_NET.

The other challenge was to logically arrange the nodes so that there is a sequential flow of the causal relationship from one generation of nodes to the other. At one point in the process of such arrangement, one of the nodes, "SolidOvrWeir", had nine "parents" which means almost 20,000 conditional probabilities were needed. This would undermine the computational advantage of the BBNs. This difficulty was largely overcome by consulting the domain experts again to rearrange some of these nine nodes into "grandparents" and "great-grandparents" by introducing intermediate common relatives.

It was an interesting process in eliciting knowledge from the two domain experts (Mr. H.A. Hawkes and Mr. P. Nungesser) to develop the CLAR_NET structure. It should be noted that both these experts were very supportive and patient in providing valuable advice. However, Mr. Hawkes resides in the U.K., and is expert in the biological area in the wastewater treatment plant; whereas Mr. Nungesser lives in the USA with his experience gained mainly from running large municipal treatment works in the USA. Both were chosen because of their expertise in wastewater treatment. The advantage of having experts from these two different background of experience was that different opinions and views could be sought, and that really enriched the author's knowledge and perspective in the wastewater treatment operations. However, since human experts tend to be biased towards their area of expertise, this could cause their judgment to be quite impartial at times. This occurred when determining the causal relationship between the nodes in developing the CLAR_NET structure.

This problem was overcome by presenting the author's own draft CLAR_NET structure to Mr. Nungesser for comment, and then elicited knowledge from him again to improve the network. After a few refinements, the revised network was then given to Mr. Hawkes for comment, and the revised draft was subsequently presented to Mr. Nungesser to get his comment and agreement. This process took a considerable amount of time since there were still some difference in opinion. Both domain experts finally agreed on the network presented in this thesis when they concluded that the network was good enough for the sake of this research work, but it should be modified according to the actual site operating configuration. For eliciting knowledge from domain expert, it is recommended that the advice of a sole expert be sought, followed by verification by other domain expert(s) on the work done. This would save considerable time and effort in the research work.

In checking the effectiveness of CLAR_NET in handling uncertainties accurately, many test methodologies were explored. One of them worth mentioning here was the "sensitivity tests" created to check the stability and sensitivity of the network as illustrated in Chapter 6. In presenting the results of the sensitivity test diagramatically in the network, it was attempted first to draw the arcs linking the nodes on different thickness to illustrate the effect of the influence. However, this method was abandoned because the effect due to evidence received is on the node itself rather than on the arc. As such, the colour coding system was adopted. The *d-connected* nodes were coloured manually to illustrate the magnitude of influence adopted and found to create a good effect on presentation of the results. In future development of CLAR_NET, a feature within the computer system can be developed so that the nodes can be shown in colour on computer screens for such sensitivity tests.

There are also many other areas which CLAR_NET could be further improved. Firstly, an 'explanation facility' which is generally considered to be an integral part of the expert systems could be developed. This could be done by introducing a user-interface system to the network, possibly by using a commercially package such as the Hypercard (Apple Computer Inc.). Hypercard, for instance, would enable CLAR_NET which was developed using ERGO computer package to be linked by the interface software. User-friendly screens could then be developed to guide users in using CLAR_NET in their diagnoses exercise. In the fast developing area of computer hardware in multimedia functions, audio visual effects can be incorporated to illustrate the effect better.

Furthermore, CLAR_NET has the potential to be further developed as a training system to enable new wastewater operators to learn about effective diagnosis of faults in activated sludge system and the wastewater treatment system as a whole. The training package, in a form of CD-ROM disk for example, could also serve as a "simulator" of an actual wastewater treatment process so that users could sharpen up their judgment in diagnosis and in prescribing corrective measures.

It is clear that CLAR_NET, and Bayesian Belief Network in general, possess great potential for future development. It is envisaged that Bayesian Belief Network will be applied more extensively in research and development.

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APPENDIX A

INFERENCE DIAGRAMS

General Notes for all Inference Diagrams

1. Unless otherwise stated on the heading of each diagram (No. 1 to 21), the symptoms indicated applies to all types of clarifiers: primary, secondary, circular and rectangular.

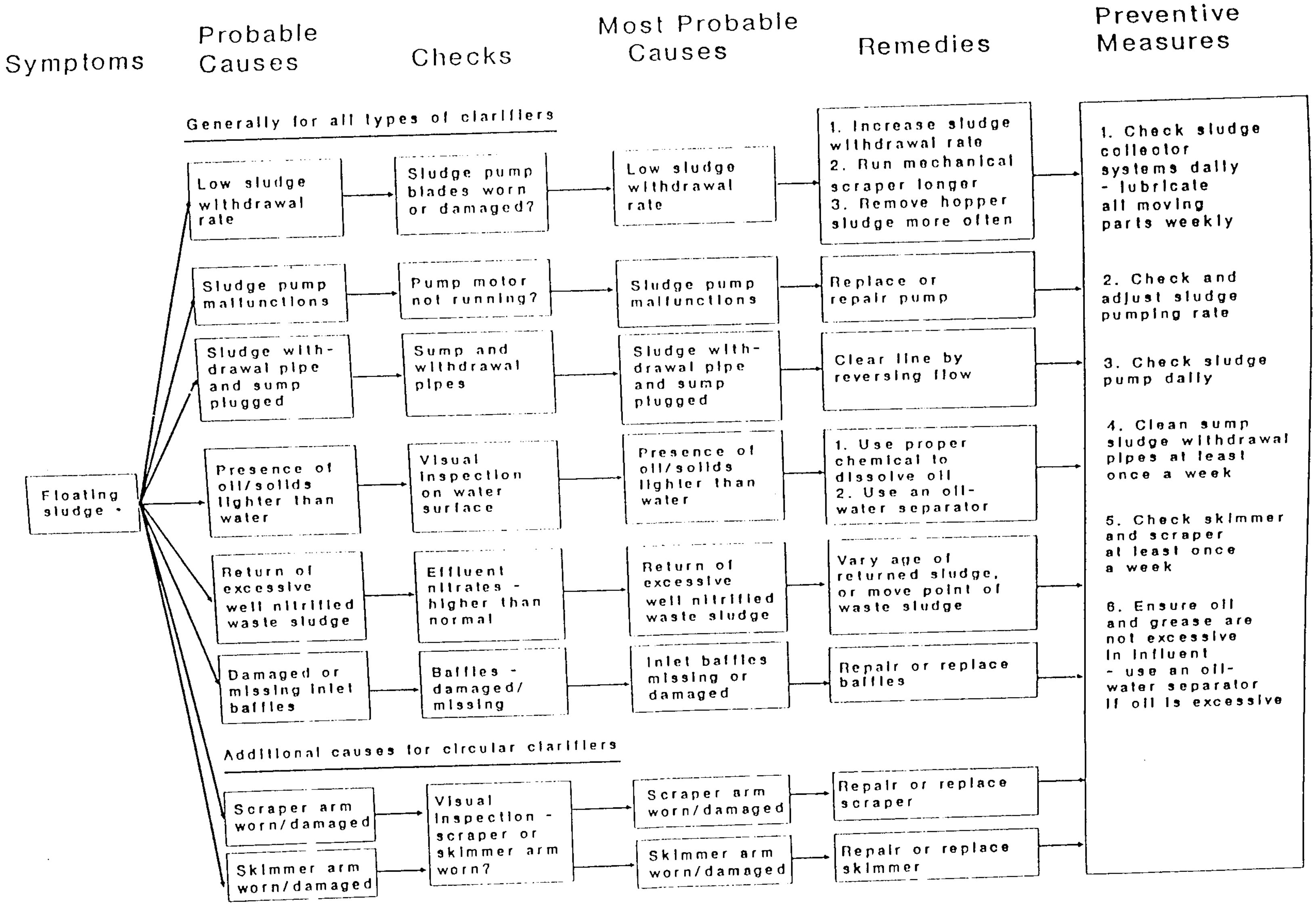
2. Tertiary type of clarifiers as noted in some texts on wastewater treatment operation are not specifically treated in the inference diagrams. They exhibit many symptoms similar to those found in primary or secondary type clarifiers, thus similar corrective measures can be taken.

3. An arrow (---->) linking an object in the "Checks" column to an object in the "Most Probable Causes" column in each inference diagram indicates a positive response as a result of the check. This means that if the check is negative, then the possible cause assumed is incorrect and another possible cause should be checked.

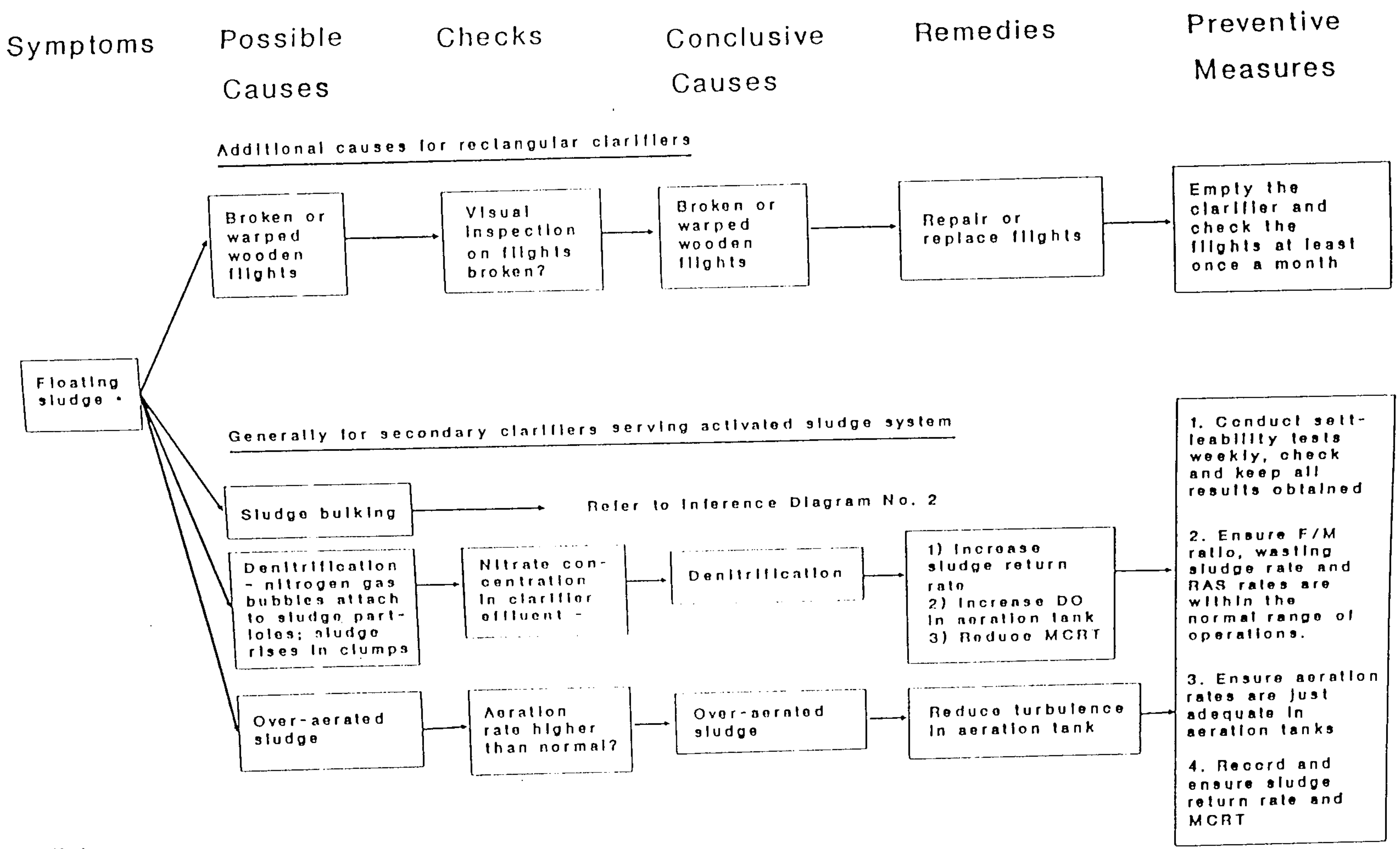
4. Abbreviations:

A.S.	=	Activated Sludge
C	=	Carbon
DO	=	Dissolved Oxygen
eq. basin	=	equalization basin
f/m ratio	=	food/microorganisms ratio
gpd	=	gallons per day
m3	=	cubic metres
MLSS	=	mixed liquor suspended solids
MLVSS	=	mixed liquor volatile suspended solids
MSDS	=	Materials Safety Data Sheet (as required by U.S. Environmental Protection Agency)
N	=	Nitrogen
P	=	Phosphorus
RAS	=	return activated sludge
RBC	=	rotating biological contactors
SVI	=	sludge volume index
TF	=	Trickling Filters
WWTP	=	wastewater treatment plant

Inference Diagram No. 1-A



Inference Diagram No. 1-B



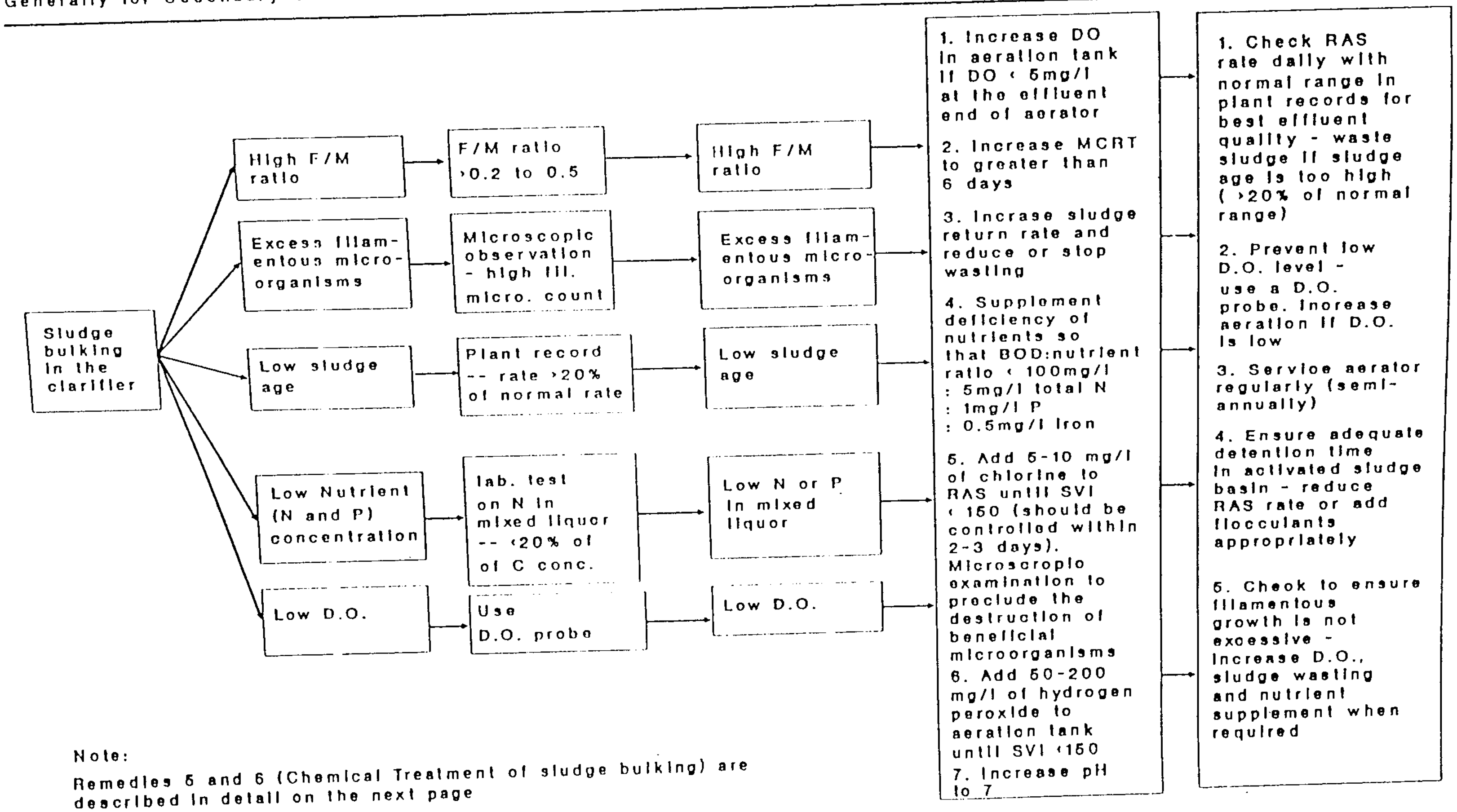
Note:

* Floating sludge occurs when sludge settles and compacts satisfactorily on the bottom of the clarifier,t after settling, it rises to the top of secondary clarifier in patches. Floating sludge produces a fine scum or froth (brown in color) on aeration basin and clarifiers

Inference Diagram No. 2A

Symptoms | Possible Causes | Checks | Most Probable Causes | Remedies | Preventive Measures

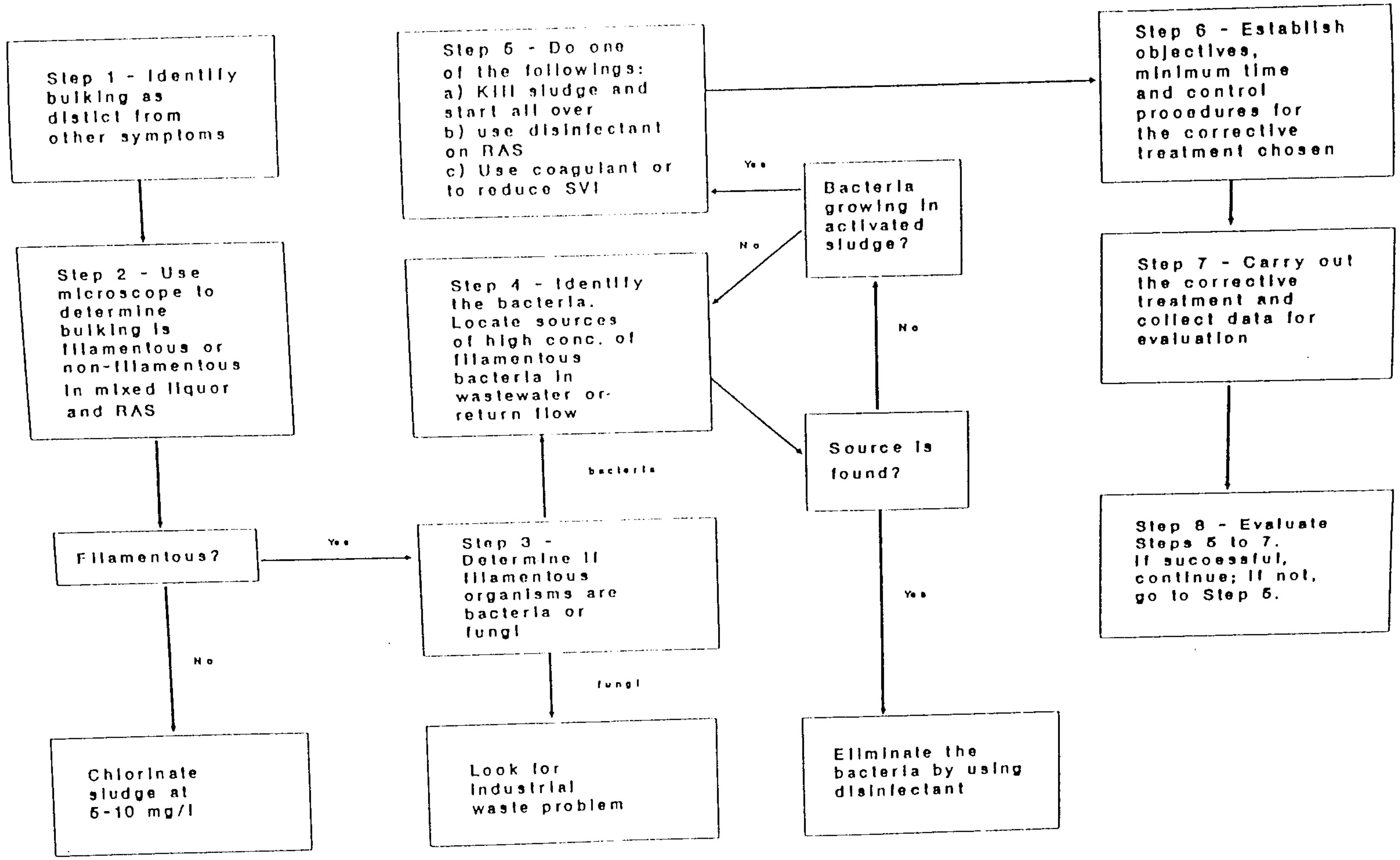
Generally for Secondary Clarifiers serving Activated Sludge system or biological package treatment plants



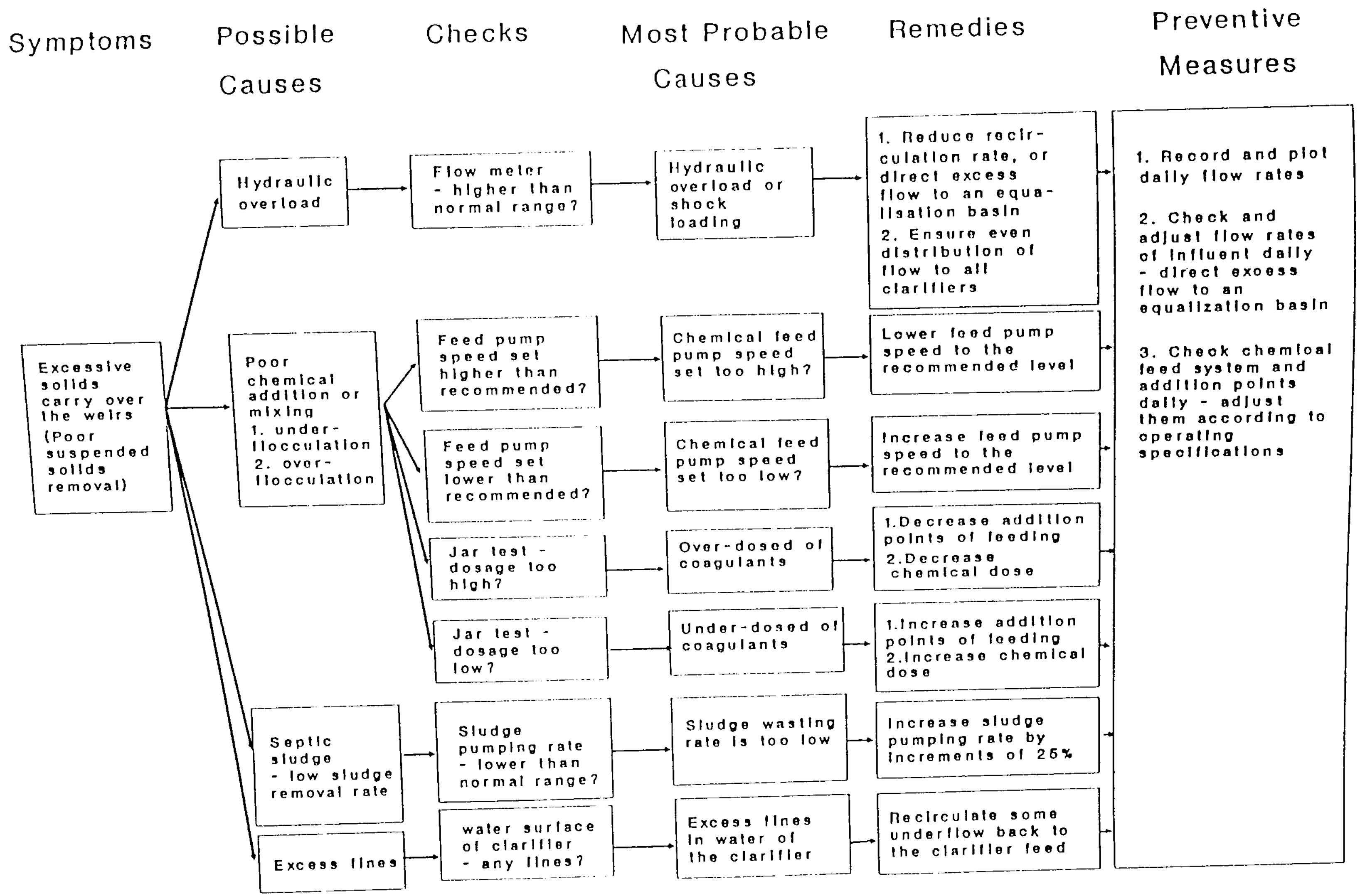
Note:
Remedies 5 and 6 (Chemical Treatment of sludge bulking) are described in detail on the next page

Inference Diagram No. 2B

• An Organised Approach to Treat Bulking Sludge Chemically (using Chlorine, Ozone, or Hydrogen Peroxide)



Inference Diagram No. 3



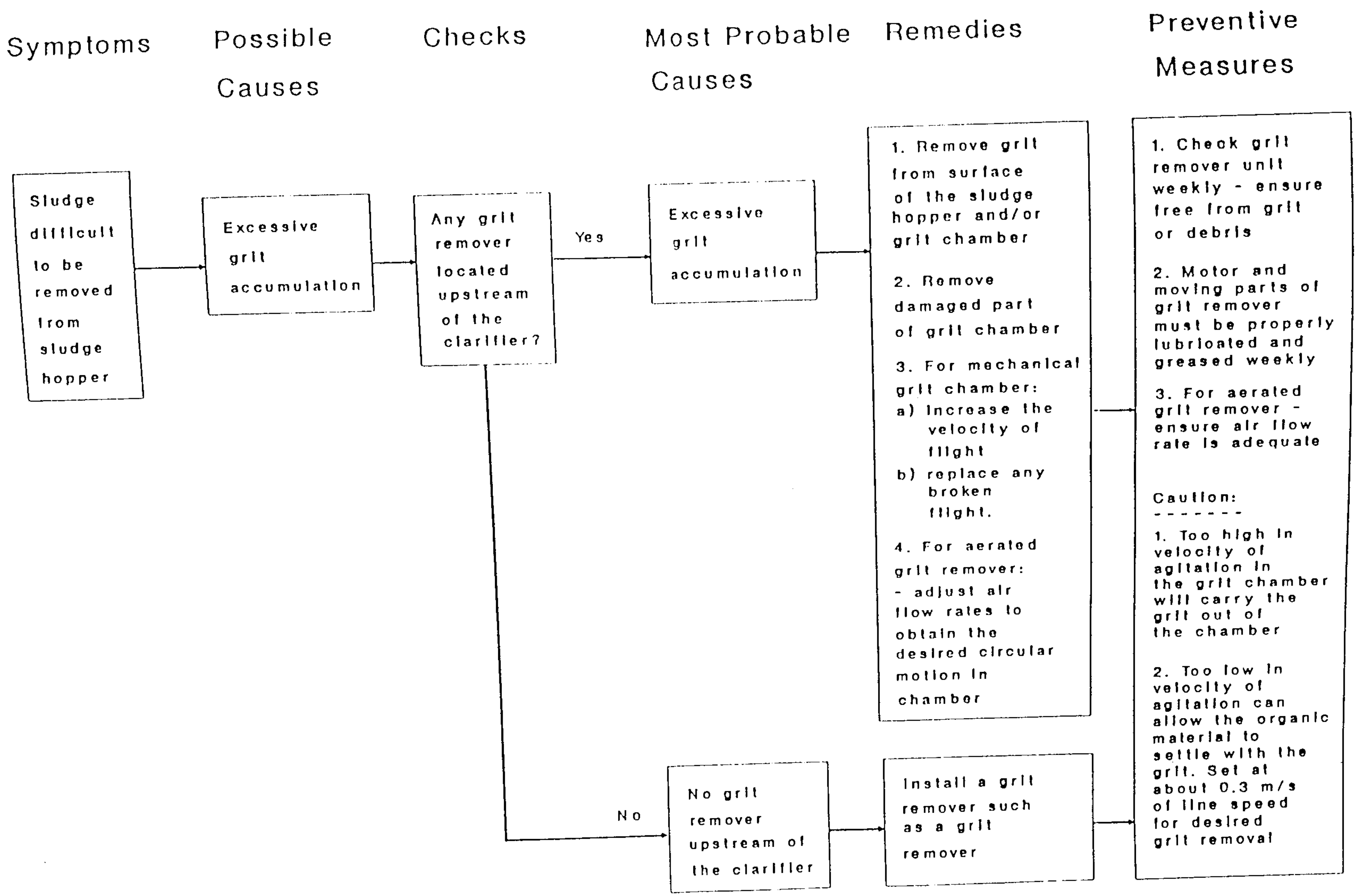
Inference Diagram No. 4

Generally for Clarifiers in Activated Sludge Systems (In addition to the causes/remedies on previous page)

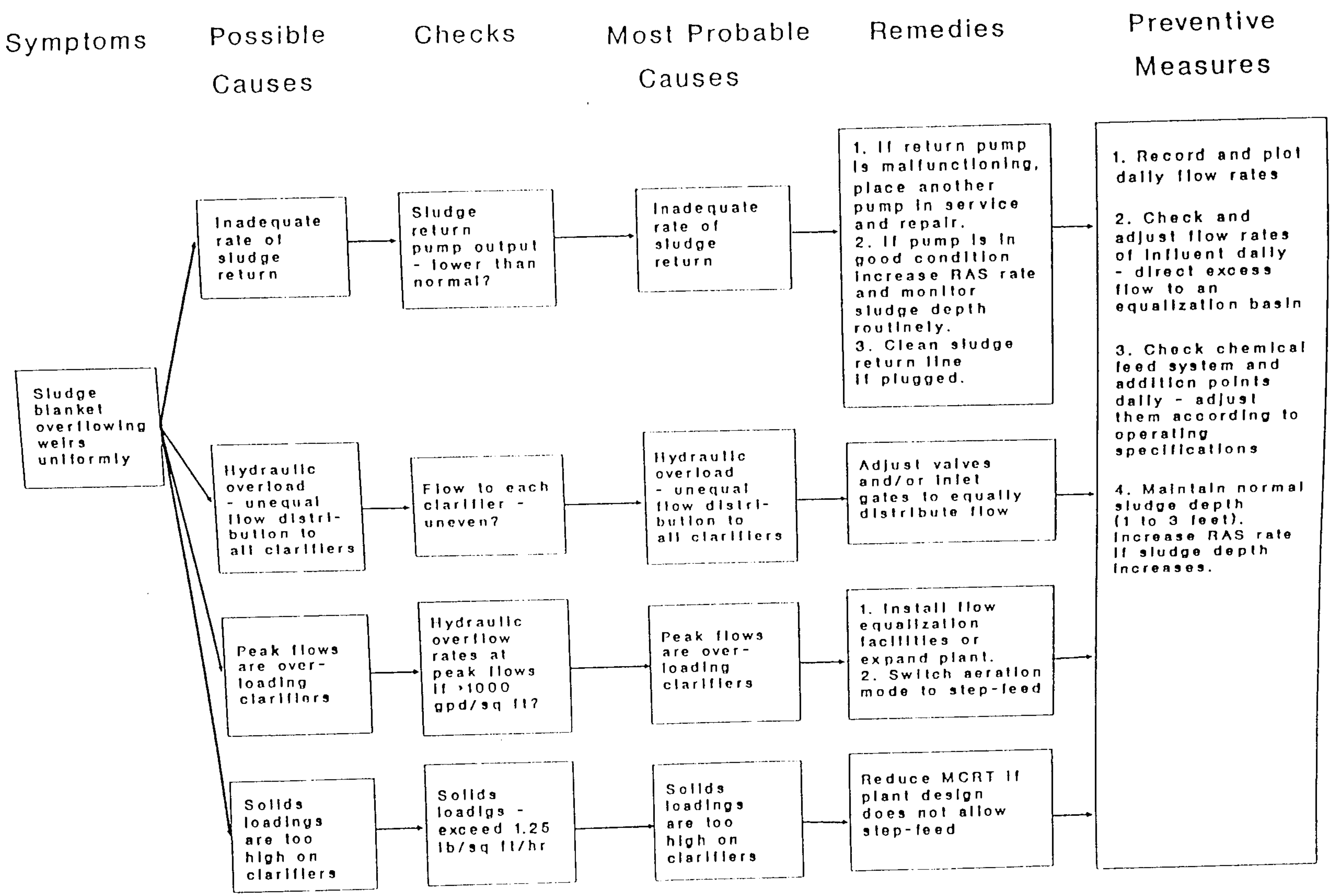
Symptoms	Possible Causes	Checks	Most Probable Causes	Remedies	Preventive Measures
Poor settling rate or floc too small (pin floc*)	Sludge age too high	Sludge removal rate lower than normal?	Sludge age too high - low sludge removal rate	Increase sludge removal rate	1. Check the F:M ratio, sludge wasting rate, and MLSS at least once a week.
	Sludge over-oxidised	Detention time higher than normal/required?	Sludge over-oxidised - high detention time	Reduce detention time by increase flow to other units	2. Ensure detention time is not higher than required
	Excess turbulence in aeration tank (results in floc shear instead of floc formation	Aerators operated longer than required?	Excess turbulence in aeration tank (results in floc shear instead of floc formation	Reduce time of aeration or stop using aerators or diffusers which cause high turbulence	3. Check aeration rate in aeration basin
	MCRT too high	MLSS - high MCRT?	MCRT too high	Increase sludge wasting rate to decrease MCRT	
	Anaerobic side stream recycled	Recycled stream anaerobic?	Anaerobic side stream recycled	Increase DO in aeration tank	
	Toxic shock load	Microscropically examine sludge for inactive protozoa	Toxic shock load	Re-seed sludge with sludge from another plant if possible; enforce industrial waste ordinaces	
	Short-circuiting of flow allowing solids to pass over weirs	Weirs - not level?	Short-circuiting of flow allowing solids to pass over weirs	Level weirs to prevent short-circuiting	

• pin flocs refer to very tiny, compact flocs of less than 0.03 inches (0.76 mm) in diameter suspended throughout moderately turbid secondary clarifier water. Pin flocs can be confirmed by running Settleability Tests in the laboratory - test is positive if rapidly settling discrete sludge particles appear granular rather than flocculent, and accumulate rather than compact, while forming a sludge blanket.

Inference Diagram No. 5



Inference Diagram No. 6



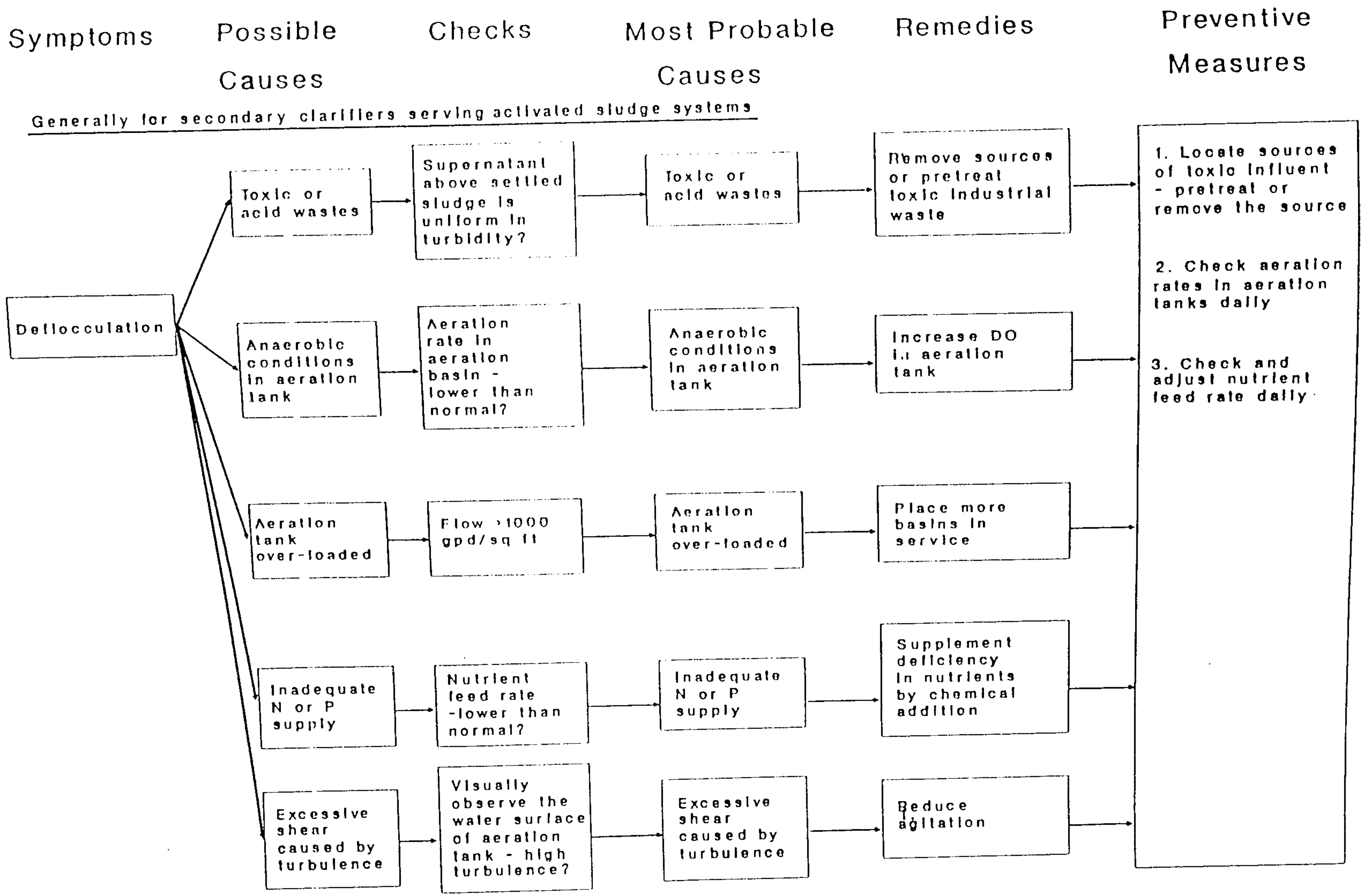
Inference Diagram No. 7

Symptoms	Possible Causes	Checks	Most Probable Causes	Remedies	Preventive Measures
Sludge blanket overflowing weirs in one portion of clarifiers	Unequal flow dis-tribution in clarifier	Effluent weirs - not level?	Unequal flow dis-tribution in clarifier	1. Level effluent weirs. 2. Dye test clarifier for short circulting and stall baffles or delectors	1. Record and plot daily flow rates 2. Maintain normal sludge depth (1 to 3 feet). Increase RAS rate if sludge depth increases. 3. Observe and correct any unequal weir level

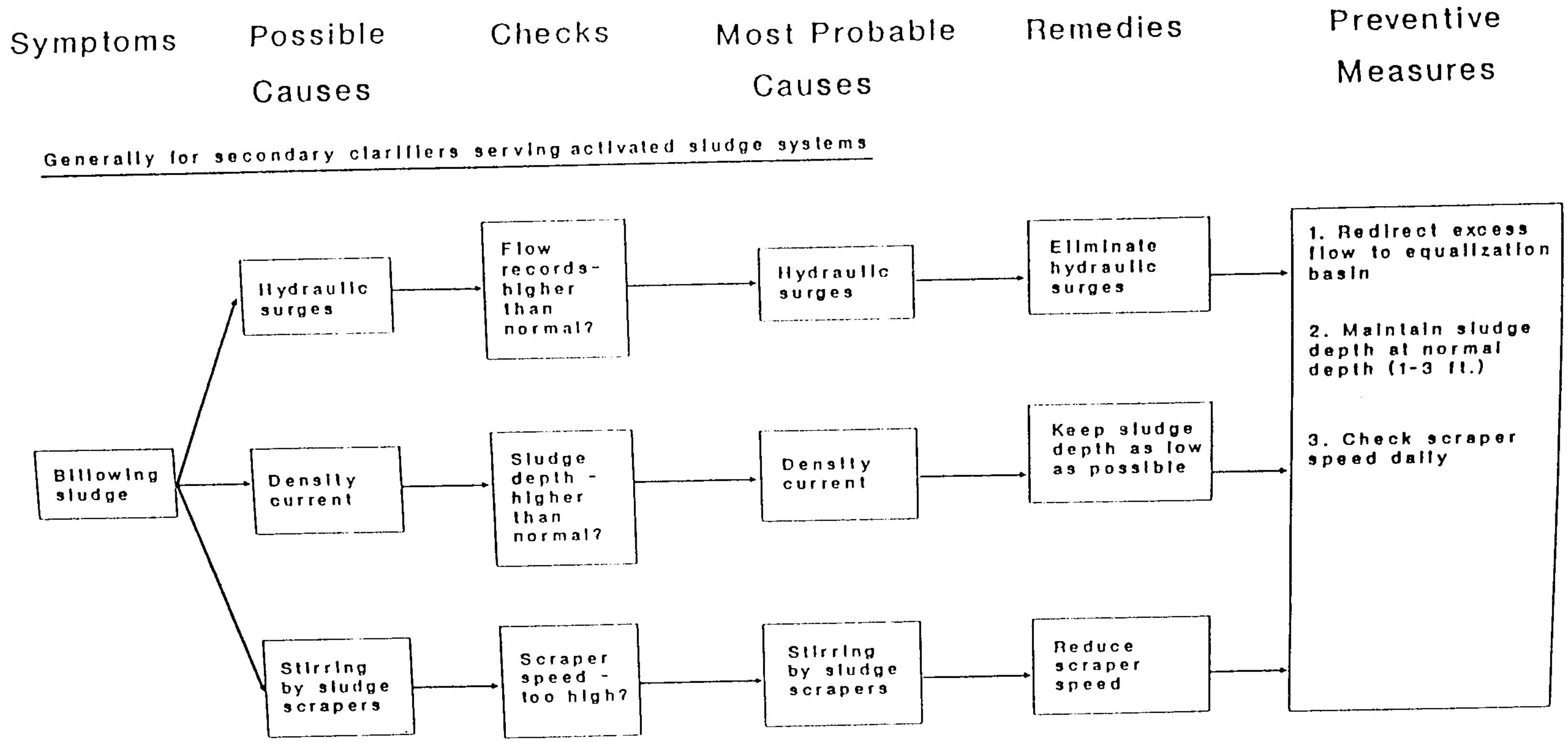
Generally for secodary clarifiers serving activated sludge systems

Symptoms	Possible Causes	Checks	Most Probable Causes	Remedies	Preventive Measures
Sludge blanket lost	Poor aeration - results in dead zones, and septic sludge	aerator contents in aeration basin turn dark? Low aeration rates?	Poor aeration - results in dead zones, and septic sludge	1. Aeration aeratopm by placing another blower in service 2. Decrease loading by placing another aeration basin in service 3. Check and repair aeration system piping for leaks 4. Clean any plugged diffusers or add more diffusers if possible 5. Increase blower CFM) output or mechanical aerator speed and depth	1. Check aeration rates in aeration basin daily. 2. Clean aerators and diffusers regularly - say once a quarter

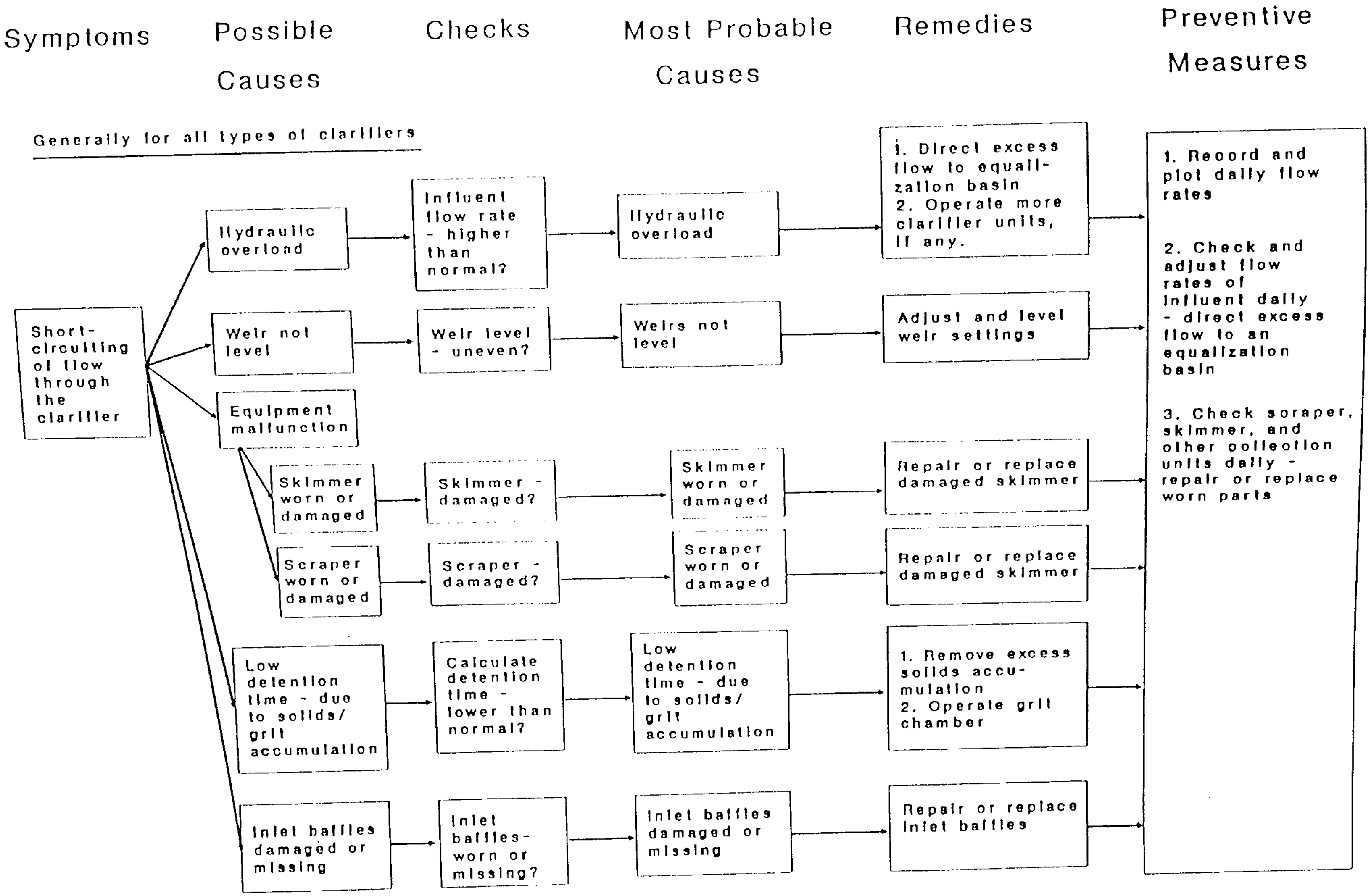
Inference Diagram No. 8



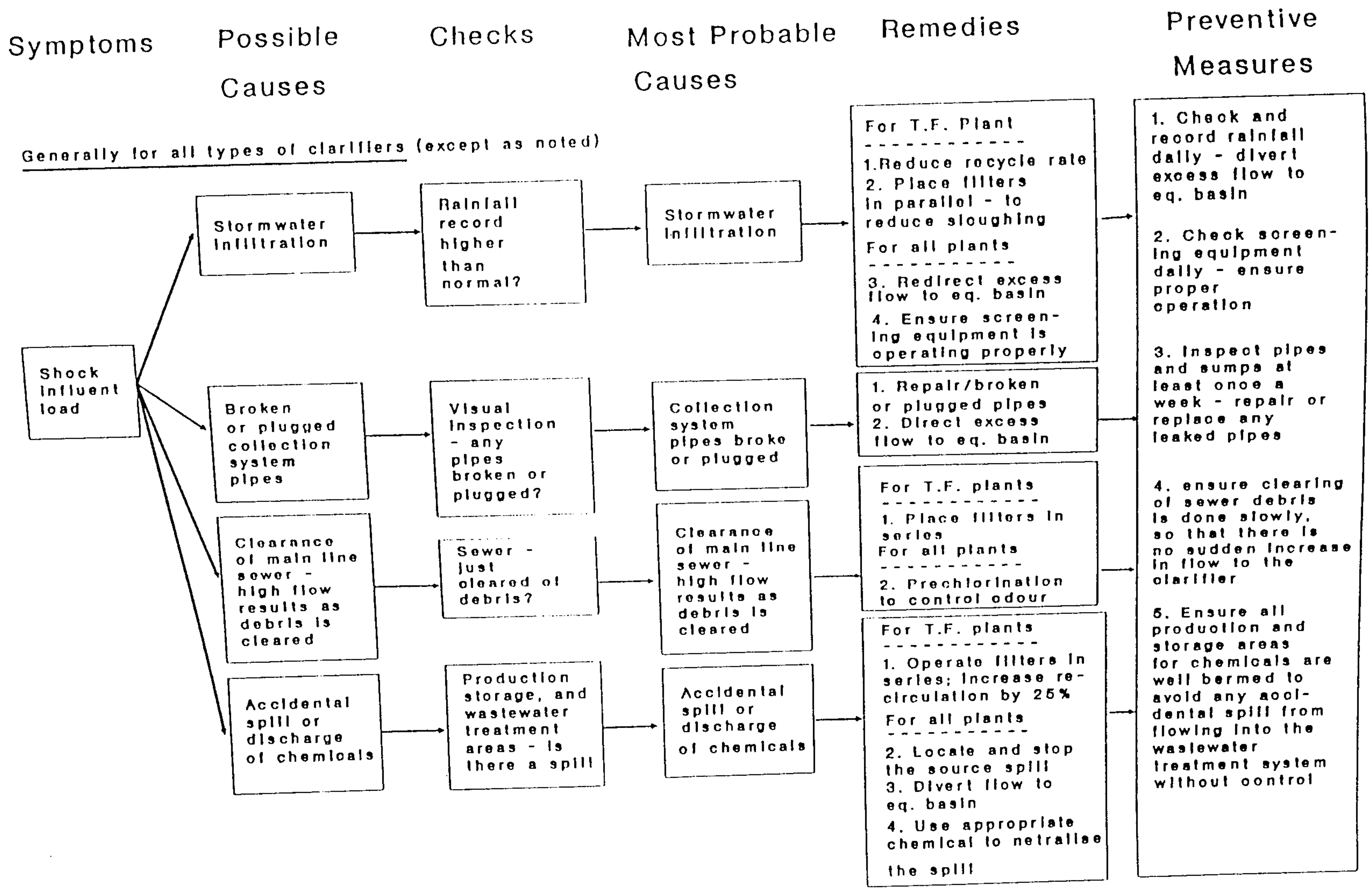
Inference Diagram No. 9



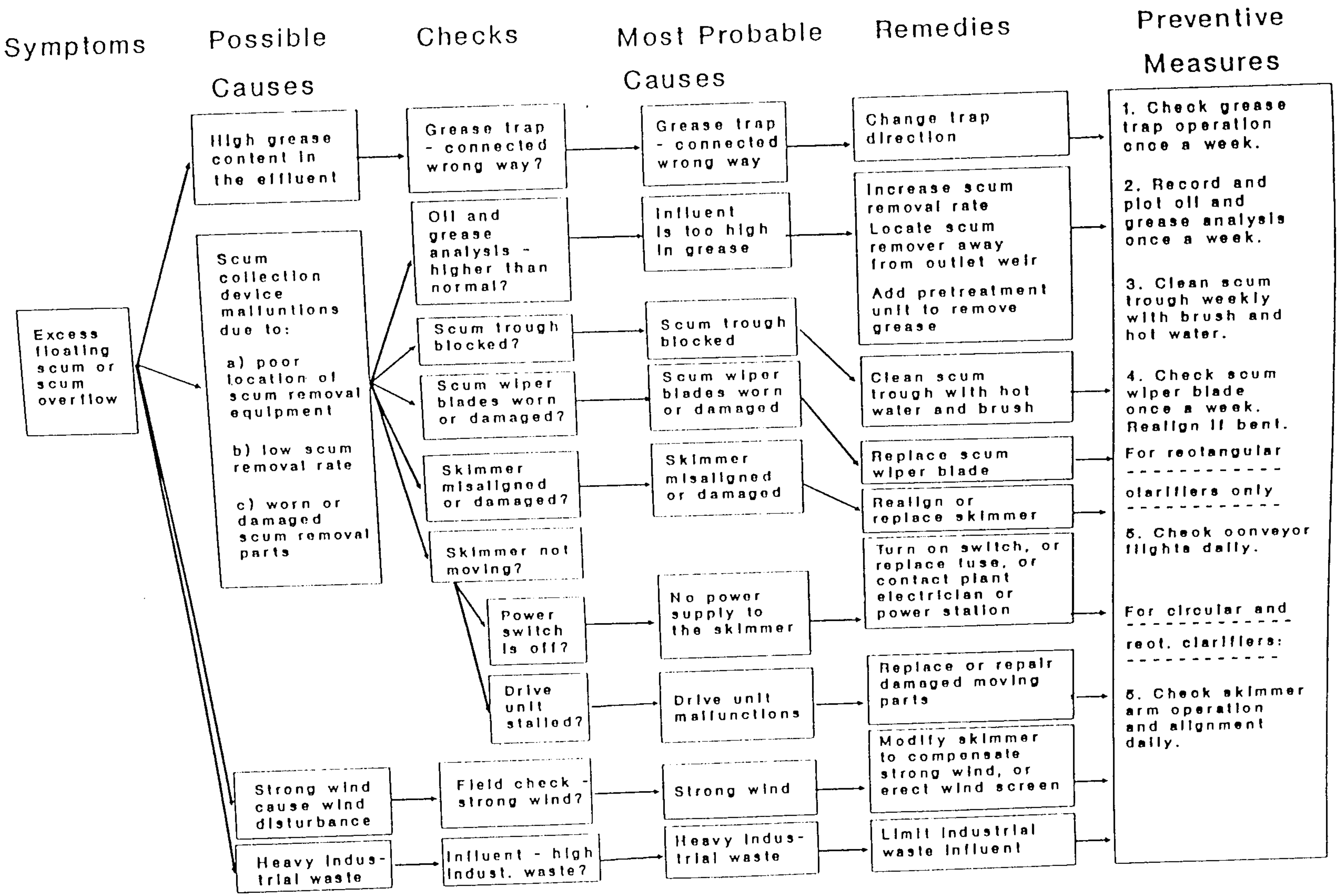
Inference Diagram No. 10



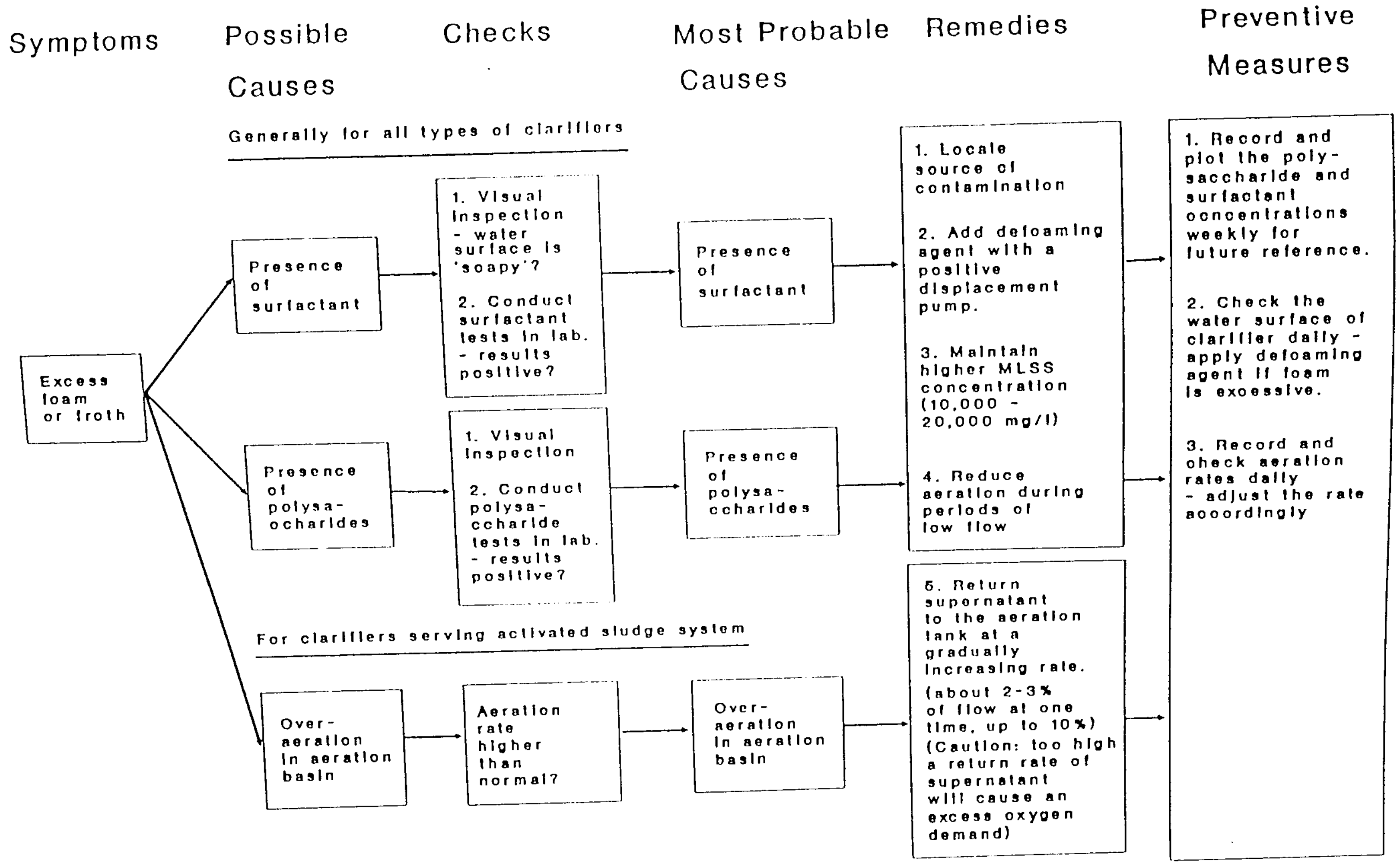
Inference Diagram No 11



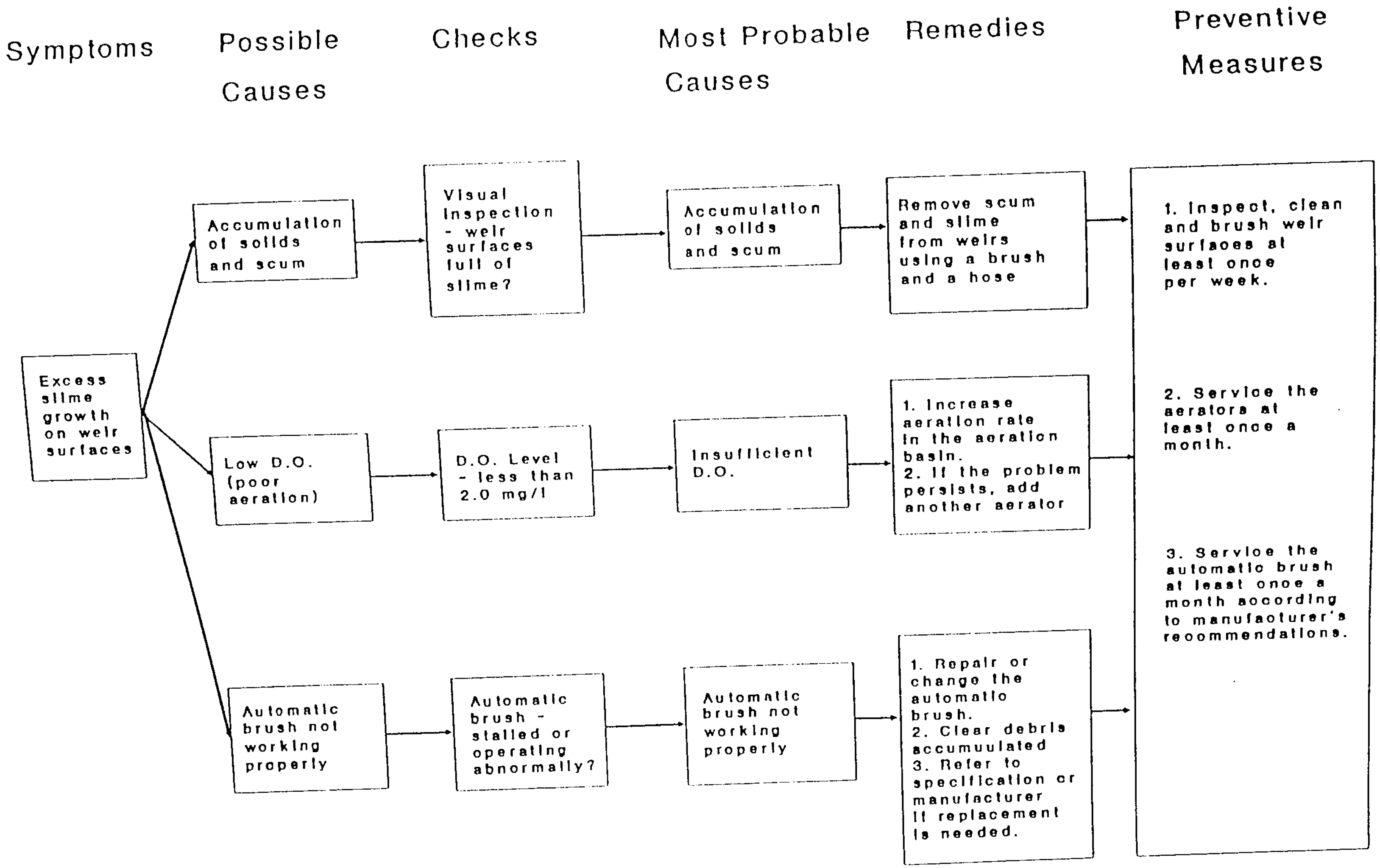
Inference Diagram No. 12



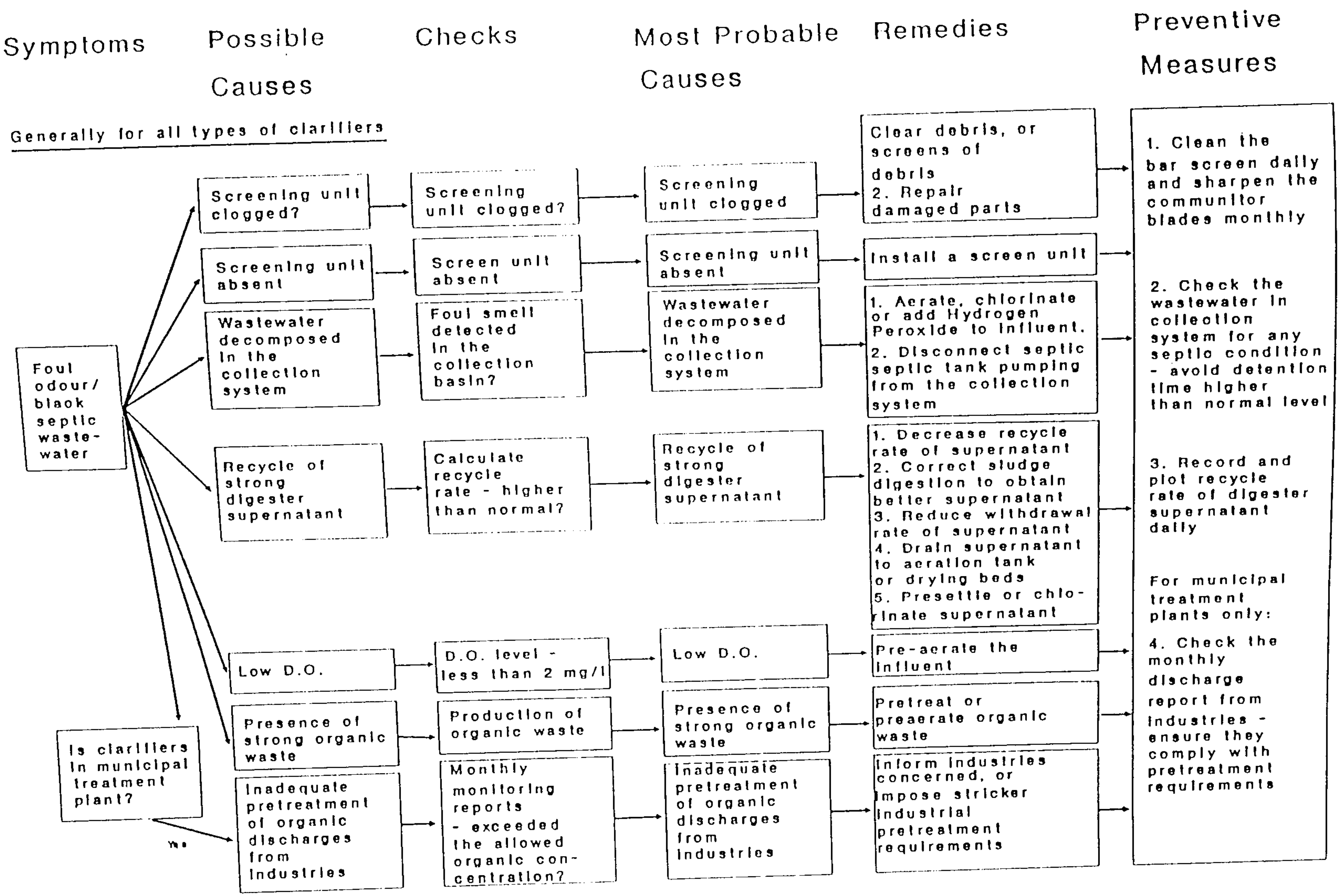
Inference Diagram No. 13



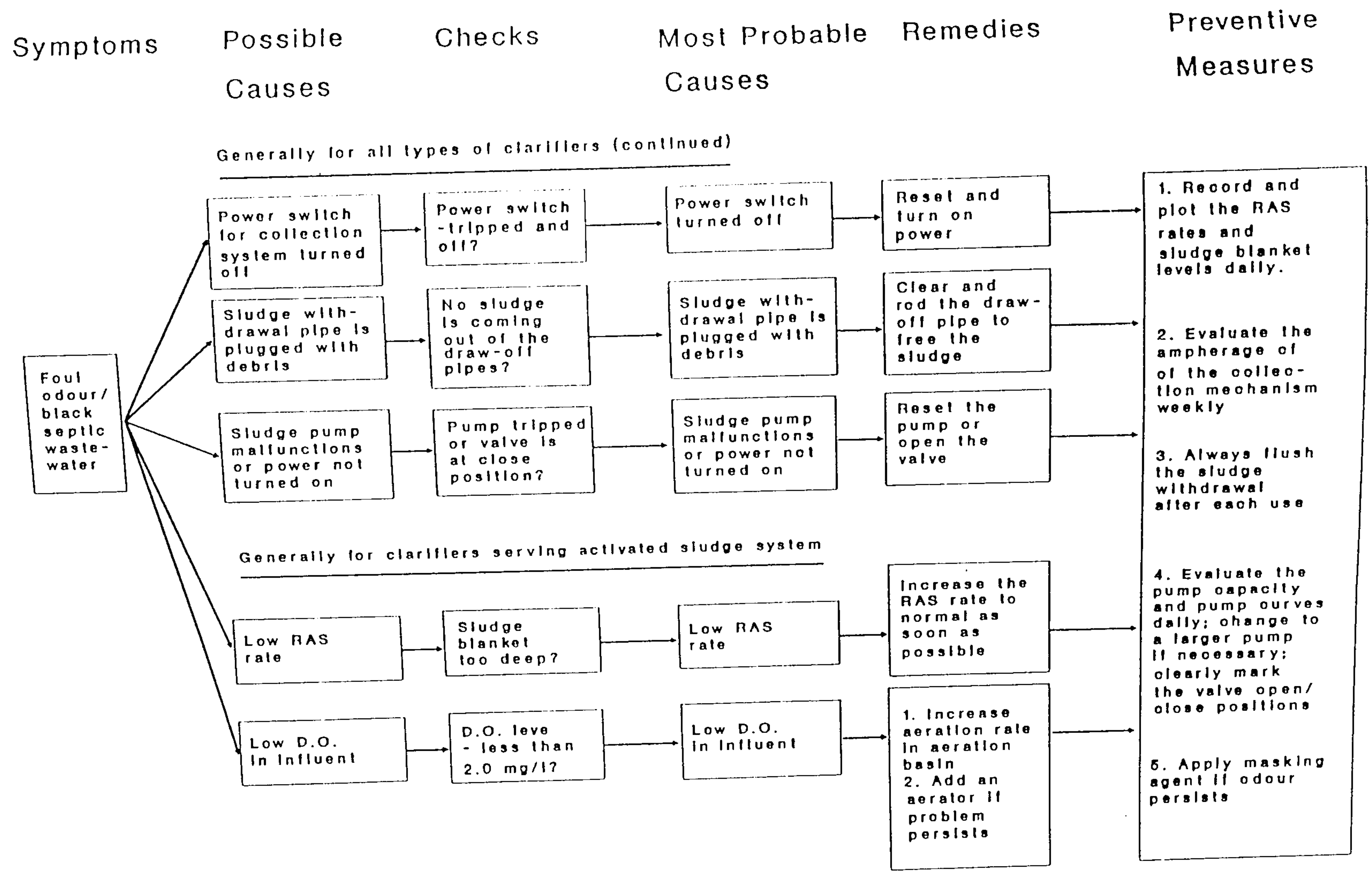
Inference Diagram No. 14



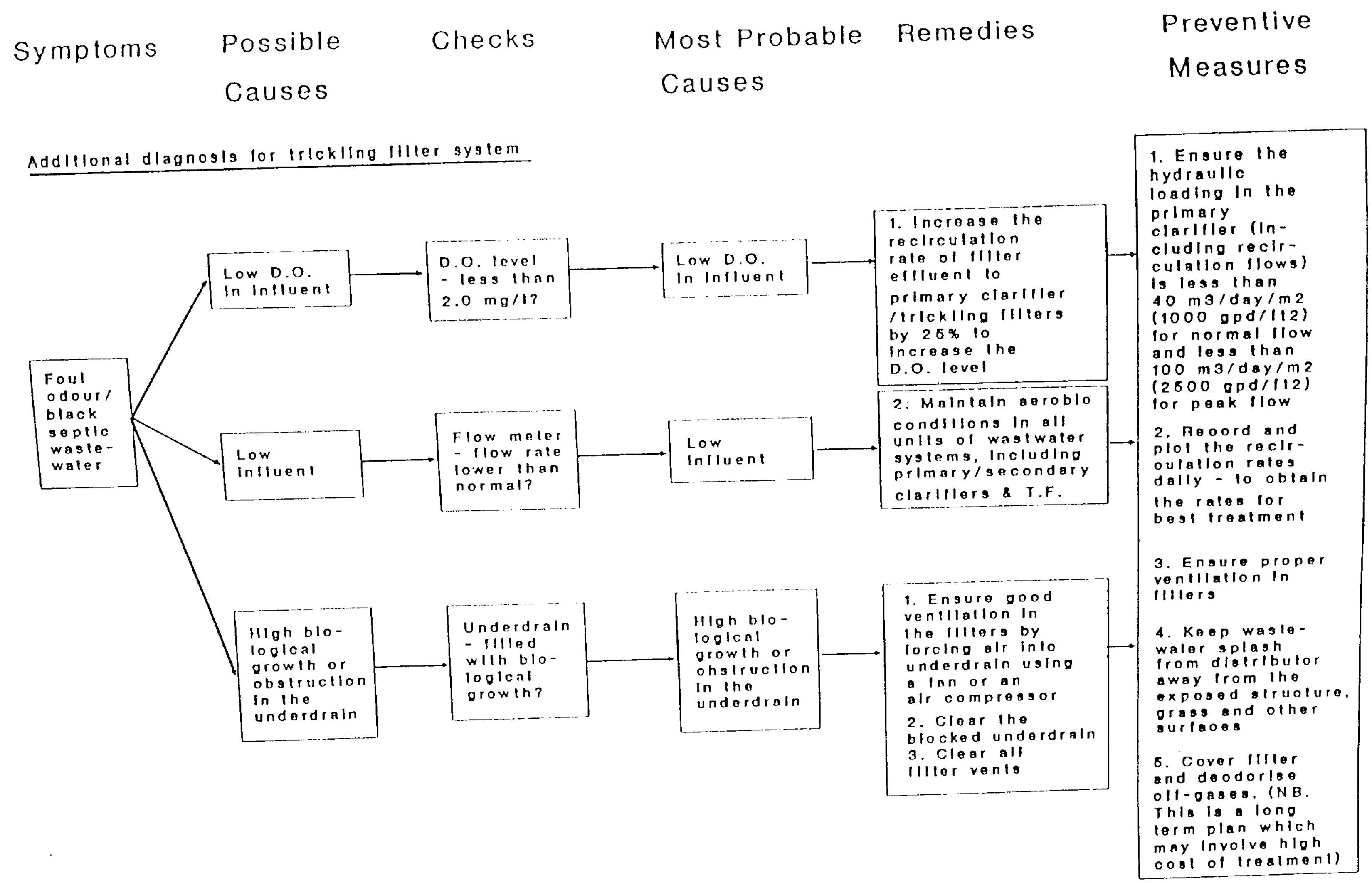
Inference Diagram No. 15A



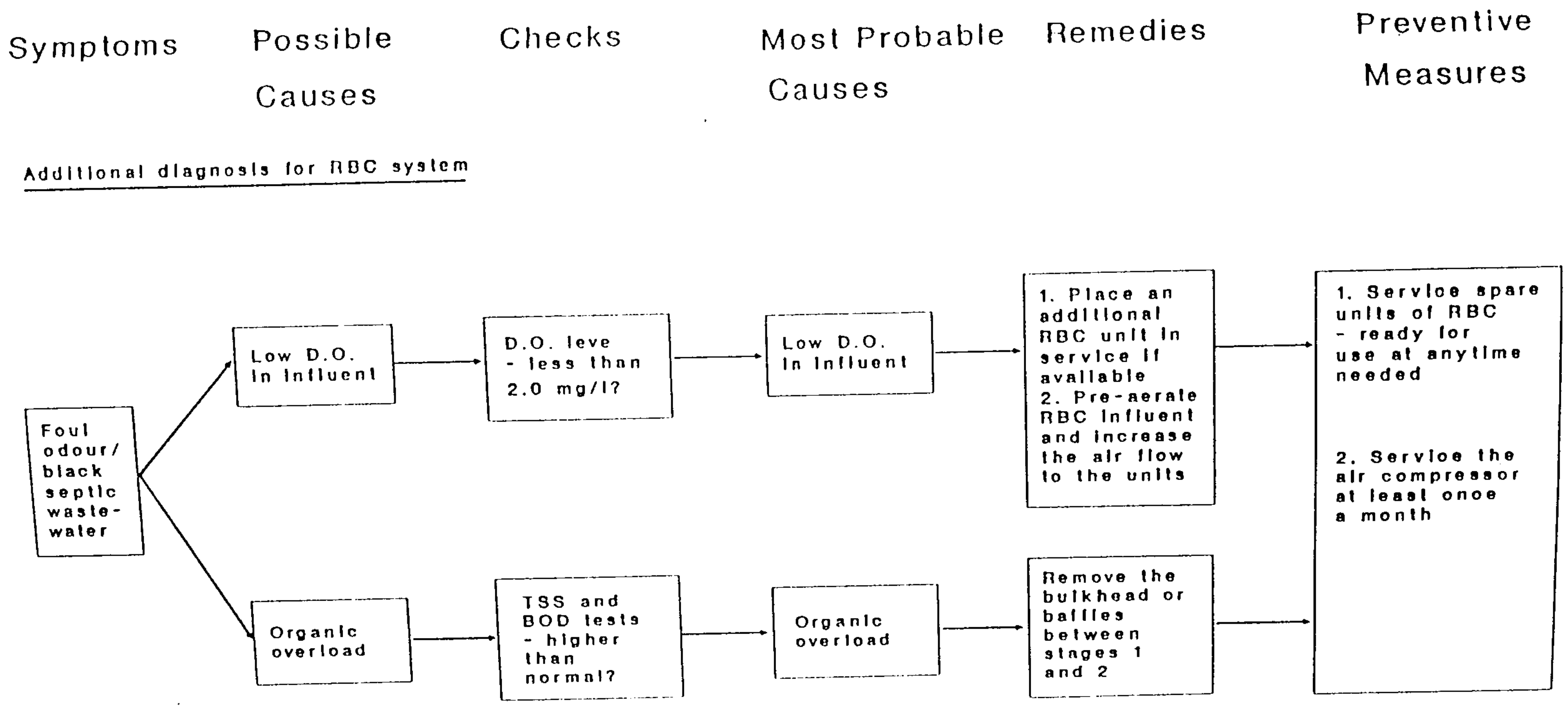
Inference Diagram No. 15B



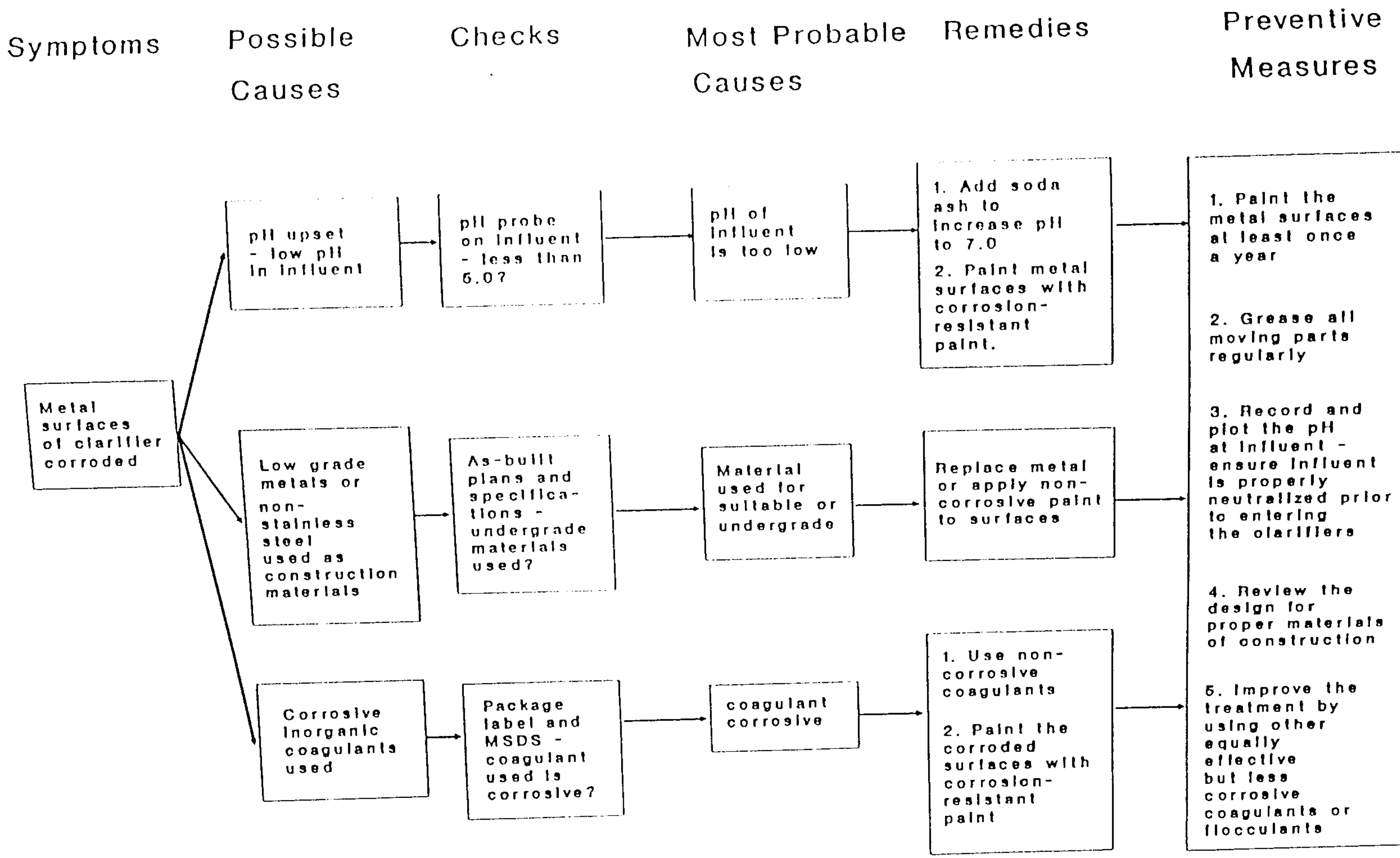
Inference Diagram No. 15C



Inference Diagram No. 15D



Inference Diagram No. 16



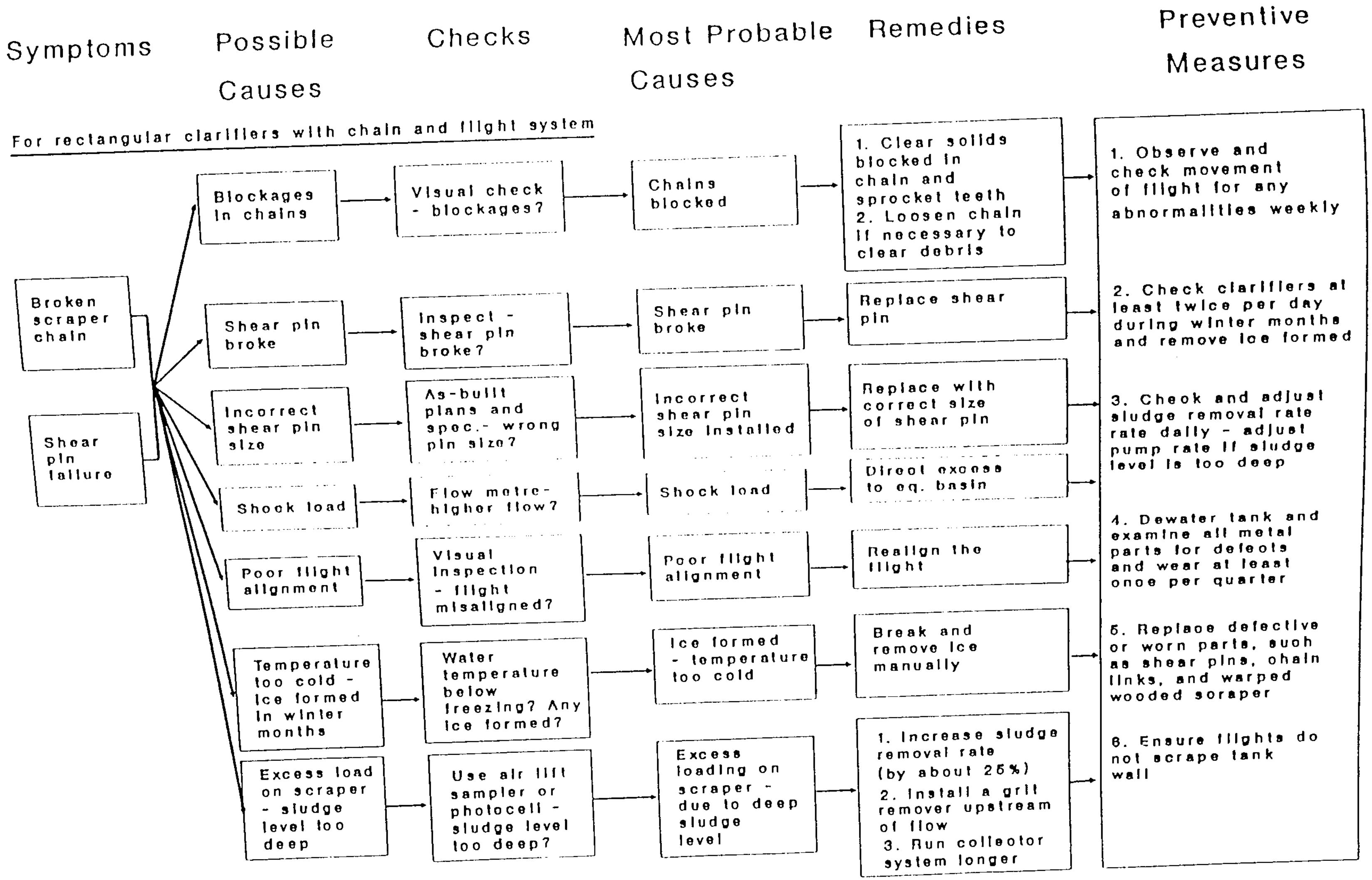
Inference Diagram No. 17

Symptoms

- Sludge collector unit jerks or jumps
- Sludge collector unit does not operate
- Overload protective switches keep tripping

Possible Causes	Checks	Most Probable Causes	Remedies	Preventive Measures
Generally for all types of clarifier				
Bad socket in drive unit	Drive unit have bad or broken sockets?	Bad socket in drive unit	Dewater the tank, then inspect and replace any bad sockets	1. Check all parts of sludge collector at least once in 3 months - including chain links, sockets, flights, and skimmer.
Sludge blanket too deep	Use air lift sampler or photocell - sludge blanket too deep?	Sludge blanket too deep	If pump works, pump out sludge; If not, remove sludge manually	2. Check and adjust the sludge pumping rate daily - ensure sludge blanket is not too deep
Pretreatment unit unable to remove solids	Pretreatment unit not available or malfunctions?	Inadequate pretreatment of influent	If pretreatment unit is avalible, clean and clear any lodged debris; add pretreatment units if none available	3. Check pretreatment units weekly - clean any debris acoumulated
For rectangular clarifiers with chain and flight				
Defective chain link	Chain link is worn or damaged?	Defective chain link	Dewater the tank, then inspect and replace the chain link	4. Store sufficient spare parts (%total) a)wear shoes - 3% b)motors - 5% c) gear reducers - 4% d)sprockets - 5% e)wall brackets - 10% f)chain pins - 6/strand g)shear pin - 10/unit
Broken flights or flights jammed by objects	Flight is broken or jammed?	Broken flights or flights jammed by objects	Dewater the tank, then inspect and repair the flight or remove lodged objects	(see 4.)

Inference Diagram No. 18

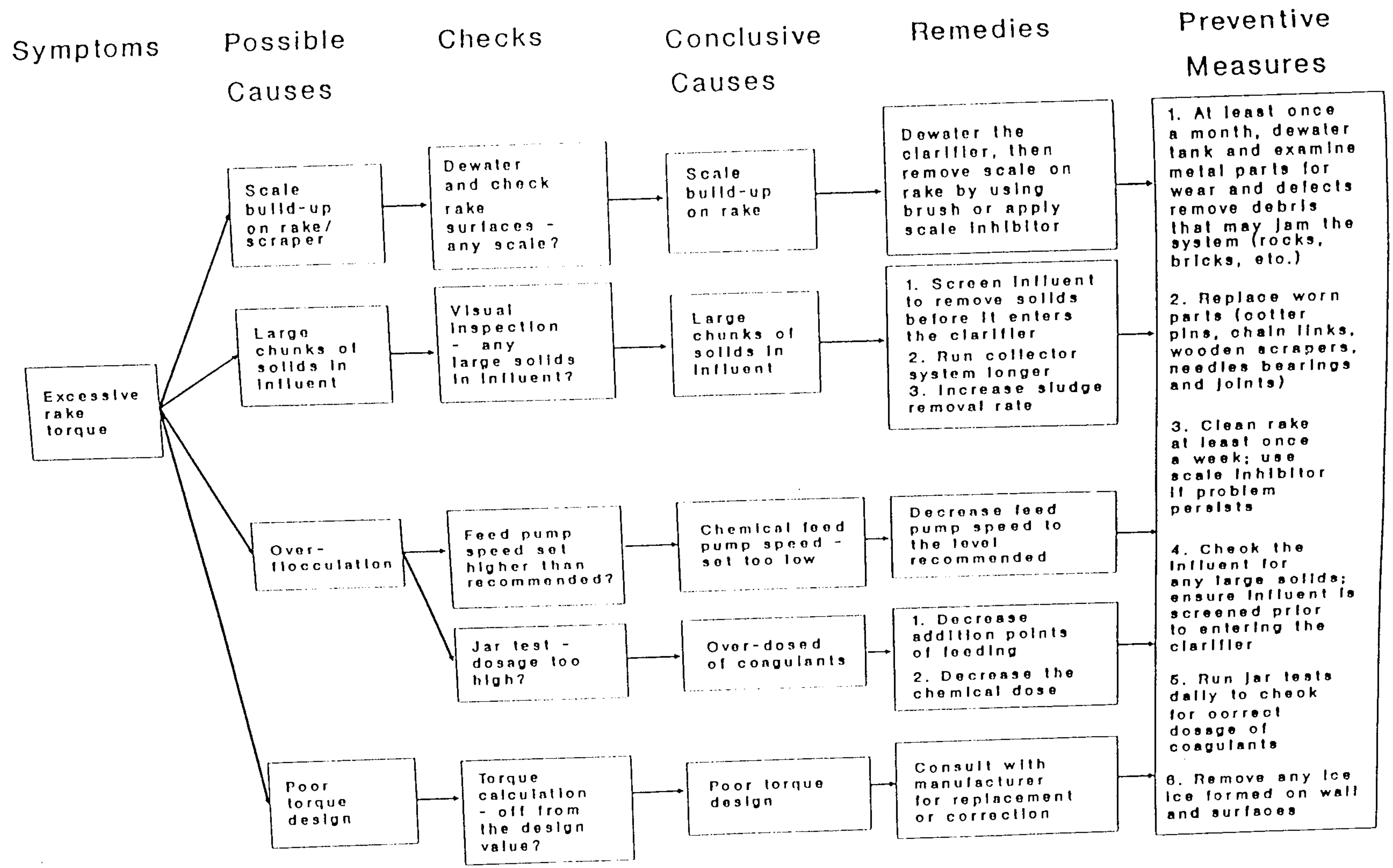


Inference Diagram No. 19

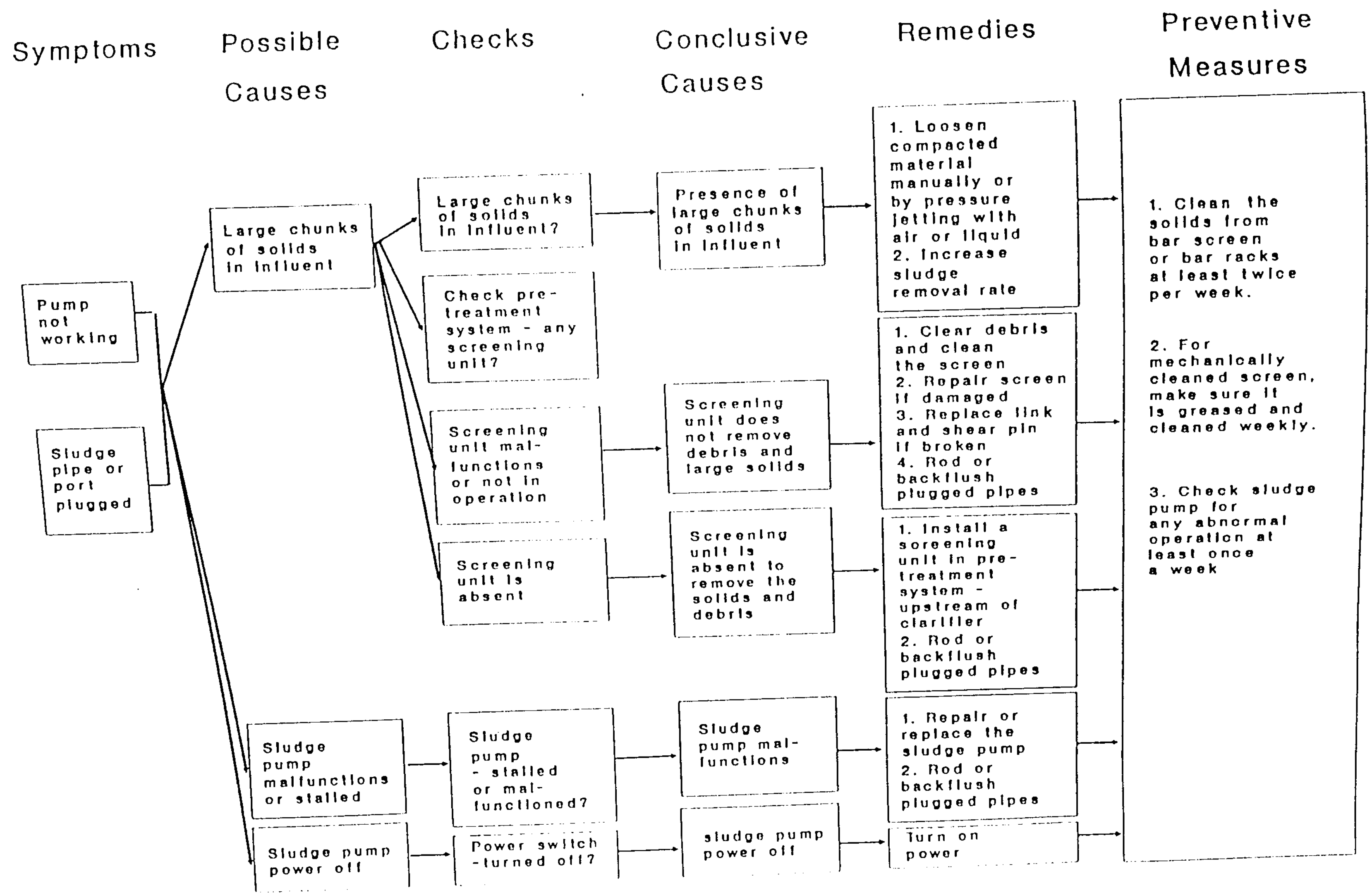
For rectangular clarifiers only - with chain & flight sludge removal type

Symptoms	Possible Causes	Checks	Most Probable Causes	Remedies	Preventive Measures
Noisy chain link; Chains that climb sprockets	Misalignment or improper assembly of drive mechanism	Drive mechanism misaligned?	Misalignment or improper assembly of drive mechanism	Realign or reassemble the drive mechanism	1. Observe and check the movement of flight and other moving parts daily for any abnormalities - replace any damaged parts immediately
	Moving parts rub against stantionary parts	Dewater the tank - moving parts rub wall?	Moving parts rub against stantionary parts	Tighten and align casing and chain. Remove dirt or other blockages.	
	Drive unit parts worn - sprockets, chains, bearings, etc.	Drive unit moving parts - any damaged?	Drive unit parts worn - sprockets, chains, bearings, etc.	Replace worn/ damaged parts - chains, bearings, sprockets, etc.	2. Lubricate all moving parts of dirve mechanism at least once a month
	Inadequate lubrication on moving parts	Maintenace record - lubrication date overdue?	Inadequate lubrication on moving parts	Lubricate all moving parts - follow suppliers' instructions.	3. Paint the metal surfaces at least once a year
	Rust or corrosion on metal surfaces of drive unit	Visual inspection on metal surfaces - any rust?	Rust or corrosion on metal surfaces of drive unit	Remove dirt dust, paint the metal, lubribcate all moving parts all moving	4. Maintain taut chain at all times
	Wrong chain size	As-built plans - wrong chain size?	Wrong chain size	Replace with correct size of chain	
	Chain loose	visual check - chain loose?	Chain loose	Tighten chain	

Inference Diagram No. 20



Inference Diagram No. 21



APPENDIX B

CLAR_EX COMPUTER CODES

```
/*************************************************************************
/*                                                                       *
/*                  CLAR_EX Version 1.0                                  *
/*                  ===================                                  *
/*                                                                       *
/*       An Expert System on Diagnosis and Remedies of Clarifier         *
/*       Operational Problems in Wastewater Treatment                    *
/*                                                                       *
/*       Developed by: Hock G. Chong                                     *
/*                                                                       *
/*************************************************************************

              control common

/*****************************************************
/*                                                   *
/*                  Declarations                     *
/*                                                   *
/*****************************************************

      if    Symptom includes x
      and   Wastewater_Type includes x
      and   Known_Pollutant includes x
      and   Chemical_Addition includes x
      then declarations are complete

/*****************************************************
/*                                                   *
/*              Get the system initialised           *
/*                                                   *
/*****************************************************

      if    start is yes
      then use screeno;
            ask Nature_of_Business;
            ask Wastewater_Type;
            ask Known_Pollutant;
            ask Clarifier_Type;
            ask Chemical_Addition;
            ask Shape;
            ask Inlet_Type;
            ask Outlet_Type;
            ask In_Tank_Baffle;
            ask Sludge_Removal_Type;
            ask Symptom;
            startstep is complete


/*****************************************************
/*                                                   *
/*          Rule for all Cause                       *
/*                                                   *
/*****************************************************

for   all Cause1
      if    startstep is complete
      and   Symptom overlaps Symptom: of Cause1
      then Likely_Cause includes Name: of Cause1
```

```
/*****************************************************
/*                                                   *
/*        Rules for Possible Causes (Screens)        *
/*                                                   *
/*****************************************************

      if Symptom includes 'floating sludge'
      then use Poss_Cause_Float_Sludge

      if Symptom includes 'sludge bulking'
      then use Poss_Cause_Bulk_Sludge

      if Symptom includes 'solids loss over weirs'
      then use Poss_Cause_Solids_Loss

      if Symptom includes 'floc too small'
      then use Poss_Cause_Small_Floc

      if Symptom includes 'floc too large'
      then use Poss_Cause_Large_floc

      if Symptom includes 'sludge accumulates in hopper'
      then use Poss_Cause_Sludge_in_Hopper

      if Symptom includes 'sludge blanket too high'
      then use Poss_Cause_High_Sludge_Blanket

      if Symptom includes 'low underflow density'
      then use Poss_Cause_Low_Underflow_Density

      if Symptom includes 'shock influent load'
      then use Poss_Cause_Shock_Influent_Load

      if Symptom includes 'excess floating scum'
      then use Poss_Cause_Floating_Scum

      if Symptom includes 'excess foam on water surface'
      then use Poss_Cause_Foam

      if Symptom includes 'excess slime on weir surfaces'
      then use Poss_Cause_Slime

      if Symptom includes 'foul odour/black septic wastewater'
      and Clarifier_Type is
      'clarifier for other type of treatment system'
      then use Poss_Cause_Foul_Odour

      if Symptom includes 'foul odour/black septic wastewater'
      and Clarifier_Type is
      'primary clarifier of an activated sludge system'
      then use Poss_Cause_AS_Foul_Odour

      if Symptom includes 'foul odour/black septic wastewater'
      and Clarifier Type is
      'secondary clarifier of an activated sludge system'
      then use Poss_Cause_AS_Foul_Odour
```

```
      if Symptom includes 'foul odour/black septic wastewater'
      and Clarifier_Type is
      'primary clarifier of a trickling filter'
      then use Poss_Cause_TF_Foul_Odour

      if Symptom includes 'foul odour/black septic wastewater'
      and Clarifier_Type is
      'secondary clarifier of a trickling filter'
      then use Poss_Cause_TF_Foul_Odour

      if Symptom includes 'foul odour/black septic wastewater'
      and Clarifier_Type is
      'primary clarifier of a rotating biological contactor'
      then use Poss_Cause_RBC_Foul_Odour

      if Symptom includes 'foul odour/black septic wastewater'
      and Clarifier_Type is
      'secondary clarifier of a rotating biological contactor'
      then use Poss_Cause_RBC_Foul_Odour

      if Symptom includes 'metal surfaces corroded'
      then use Poss_Cause_Corrosion

      if Symptom includes 'sludge collector jerks/jumps/stalls'
      then use Poss_Cause_Jerking_Collector

      if Symptom includes 'overload protective switch trips'
      then use Poss_Cause_Switch_Trips

      if Symptom includes 'broken scraper chain/shear pin failure'
      and Sludge_Removal_Type is 'chain & flight'
      then use Poss_Cause_Broken_Chain

      if Symptom includes 'noisy chain or chains climb sprockets'
      and Sludge_Removal_Type is 'chain & flight'
      then use Poss_Cause_Noisy_Chain

      if Symptom includes 'excessive rake torque'
      then use Poss_Cause_Excess_Torque

      if Symptom includes 'sludge pump or pipe fails/plugged'
      then use Poss_Cause_Plugged_Pipes


/*****************************************************
/*                                                   *
/*                  Rules for Checks                 *
/*                                                   *
/*****************************************************

/*****************************************************
/*      *** Rules to Check 'floating sludge' ***     *
/*****************************************************

      if Symptom includes 'floating sludge'
      and Check_Collector_Fails is Yes
      then Check includes 'collector fails'

      if Symptom includes 'floating sludge'
```

```
       and Check_Sludge_Withdraw_Low is Yes
       then Check includes 'sludge withdraw low'

       if Symptom includes 'floating sludge'
       and Check_Sludge_Pump_Fails is Yes
       then Check includes 'pump fails'

       if Symptom includes 'floating sludge'
       and Check_Sludge_Pipe_Plugged is Yes
       then Check includes 'pipe or sump plugged'

       if Symptom includes 'floating sludge'
       and Check_Skimmer_Worn is Yes
       then Check includes 'skimmer fails'

       if Symptom includes 'floating sludge'
       and Check_Scraper_Worn is Yes
       then Check includes 'scraper fails'

       if Symptom includes 'floating sludge'
       and Check_Oil_Presence is Yes
       then Check includes 'oil present'

       if Symptom includes 'floating sludge'
       and Check_SVI_Out_Of_Range is Yes
       then Check includes 'SVI out of range'

       if Symptom includes 'floating sludge'
       and Check_Detent_Time_Long is Yes
       then Check includes 'long detention time'

/*****************************************************
/*       *** Rules to Check 'sludge bulking' ***     *
/*****************************************************

       if Symptom includes 'sludge bulking'
       and Check_RAS_Rate_High is Yes
       then Check includes 'high RAS'

       if Symptom includes 'sludge bulking'
       and Check_DO_Low is Yes
       then Check includes 'low DO'

       if Symptom includes 'sludge bulking'
       and Check_FM_High is Yes
       then Check includes 'high FM'

       if Symptom includes 'sludge bulking'
       and Check_pH_Low is Yes
       then Check includes 'low pH'

       if Symptom includes 'sludge bulking'
       and Check_N_Conc_Low is Yes
       then Check includes 'low N conc'

       if Symptom includes 'sludge bulking'
       and Check_Filamentous_Bacteria is Yes
       then Check includes 'filamentous bacteria'
```

```
/*****************************************************
/*   *** Rules to Check 'solids loss over weirs' ***  *
/*****************************************************

        if    Symptom includes 'solids loss over weirs'
        and   Check_Hyd_Overload is Yes
        then  Check includes 'hydraulic overload'

        if    Symptom includes 'solids loss over weirs'
        and   Check_Feed_Rate_High is Yes
        then  Check includes 'high feed rate'

        if Symptom includes 'solids loss over weirs'
        and Check_Feed_Rate_High is No
        and Check_Feed_Rate_Low is Yes
        then Check includes 'low feed rate'

        if Symptom includes 'solids loss over weirs'
        and Check_Sludge_Withdraw_Low is Yes
        then Check includes 'sludge withdraw low'

        if Symptom includes 'solids loss over weirs'
        and Check_Excess_Fines is Yes
        then Check includes 'excess fines'

        if Symptom includes 'solids loss over weirs'
        and Check_RAS_Rate_Low is Yes
        then Check includes 'low RAS'

        if Symptom includes 'solids loss over weirs'
        and Check_Influent_Toxic is Yes
        then Check includes 'toxic discharge'

/*****************************************************
/*    *** Rules to Check 'poor settling rate          *
/*                         or floc too small' ***     *
/*****************************************************

        if Symptom includes 'floc too small'
        and Check_Hyd_Overload is Yes
        then Check includes 'hydraulic overload'

        if Symptom includes 'floc too small'
        and Check_Rake_Speed_Fast is Yes
        then Check includes 'fast rake speed'

        if Symptom includes 'floc too small'
        and Check_Feed_Rate_Low is Yes
        then Check includes 'low feed rate'

        if Symptom includes 'floc too small'
        and Check_Dosage_Low is Yes
        then Check includes 'low dosage'

        if Symptom includes 'floc too small'
        and Check_Baffles_Misaligned is Yes
        then Check includes 'baffles misaligned'

        if Symptom includes 'floc too small'
```

```
      and Check_Paddle_Speed_Fast is Yes
      then Check includes 'fast paddle speed'

      if Symptom includes 'floc too small'
      and Check_SVI_Out_Of_Range is Yes
      then Check includes 'SVI out of range'

/**************************************************
/*      *** Rules to Check 'floc too large' ***         *
/**************************************************

      if Symptom includes 'floc too large'
      and Check_Influent_Low is Yes
      then Check includes 'influent low'

      if Symptom includes 'floc too large'
      and Check_Rake_Speed_Slow is Yes
      then Check includes 'slow rake speed'

      if Symptom includes 'floc too large'
      and Check_Feed_Rate_High is Yes
      then Check includes 'high feed rate'

      if Symptom includes 'floc too large'
      and Check_Dosage_High is Yes
      then Check includes 'high dosage'

      if Symptom includes 'floc too large'
      and Check_Paddle_Speed_Slow is Yes
      then Check includes 'low paddle speed'

/**************************************************
/*  Rules to Check 'sludge accumulates in hopper'   *
/**************************************************


      if Symptom includes 'sludge accumulates in hopper'
      and Check_Grit_Rem_Malfunction is Yes
      then Check includes 'grit remover fails'


      if Symptom includes 'sludge accumulates in hopper'
      and Check_Grit_Rem_Absent is Yes
      then Check includes 'grit remover absent'

/**************************************************
/*  *** Rules to Check 'low underflow density'  ***  *
/**************************************************

      if Symptom includes 'low underflow density'
      and Check_Hyd_Overload is Yes
      then Check includes 'hydraulic overload'

      if Symptom includes 'low underflow density'
      and Check_Dosage_Low is Yes
      then Check includes 'low dosage'

      if Symptom includes 'low underflow density'
      and Check_Feed_Rate_Low is Yes
```

```
    then Check includes 'low feed rate'

    if Symptom includes 'low underflow density'
    and Check_Baffles_Misaligned is Yes
    then Check includes 'baffles misaligned'

/****************************************************
/*   *** Rules to Check 'shock influent load' ***   *
/****************************************************

    if Symptom includes 'shock influent load'
    and Check_Rain_infiltration is Yes
    then Check includes 'rain infiltration'

    if Symptom includes 'shock influent load'
    and Check_Broken_Coll_Pipe is Yes
    then Check includes 'collection pipe broken'

    if Symptom includes 'shock influent load'
    and Check_Clearing_Sewer is Yes
    then Check includes 'sewer just cleared'

    if Symptom includes 'shock influent load'
    and Check_Toxic_Discharge is Yes
    then Check includes 'toxic discharge'

/****************************************************
/* *** Rules to Check 'excess floating scum' ***    *
/****************************************************

    if Symptom includes 'excess floating scum'
    and Check_Grease_Trap_Wrong is Yes
    then Check includes 'grease trap wrong way'

    if Symptom includes 'excess floating scum'
    and Check_Greasy_Influent is Yes
    then Check includes 'influent greasy'

    if Symptom includes 'excess floating scum'
    and Check_Scum_Trough_Blocked is Yes
    then Check includes 'blocked scum trough'

    if Symptom includes 'excess floating scum'
    and Check_Scum_Wiper_Worn is Yes
    then Check includes 'scum wiper worn'

    if Symptom includes 'excess floating scum'
    and Check_Skimmer_Worn is Yes
    then Check includes 'skimmer fails'

    if Symptom includes 'excess floating scum'
    and Check_Skimmer_Not_Moving is Yes
    and Check_Drive_Power_Off is Yes
    then Check includes 'drive power switch off'

    if Symptom includes 'excess floating scum'
    and Check_Skimmer_Not_Moving is Yes
    and Check_Drive_Unit_Stalled is Yes
    then Check includes 'drive unit stalled'
```

```
/*****************************************************
/* ** Rules to Check 'excess foam on water surface'***
/*****************************************************


      if Symptom includes 'excess foam on water surface'
      and Check_Surfactant is Yes
      then Check includes 'surfactant present'

      if Symptom includes 'excess foam on water surface'
      and Check_Polysaccharides is Yes
      then Check includes 'polysaccharides present'

      if Symptom includes 'excess foam on water surface'
      and Clarifier_type is
      'primary clarifier of an activated sludge system'
      and Check_Over_Aeration is Yes
      then Check includes 'over aeration'

      if Symptom includes 'excess foam on water surface'
      and Clarifier_type is
      'secondary clarifier of an activated sludge system'
      and Check_Over_Aeration is Yes
      then Check includes 'over aeration'

      if Symptom includes 'excess foam on water surface'
      and Clarifier_type is
      'clarifier of a package plant treatment system'
      and Check_Over_Aeration is Yes
      then Check includes 'over aeration'

      if Symptom includes 'excess foam on water surface'
      and Clarifier_type is
      'clarifier for other type of treatment system'
      and Check_Over_Aeration is Yes
      then Check includes 'over aeration'


/*****************************************************
/* * Rules to Check 'excess slime on weir surfaces'* *
/*****************************************************

      if Symptom includes 'excess slime on weir surfaces'
      and Check_Solids_on_Weirs is Yes
      then Check includes 'solids on weirs'

      if Symptom includes 'excess slime on weir surfaces'
      and Check_DO_Low is Yes
      then Check includes 'low DO'

      if Symptom includes 'excess slime on weir surfaces'
      and Check_AutoBrush_Malfunction is Yes
      then Check includes 'autobrush malfunctions'
```

```
/*******************************************************
/* *** Rules to Check 'foul odour/black septic          *
/*                       wastewater' ***                *
/*******************************************************

      if Symptom includes 'foul odour/black septic wastewater'
      and Check_Bar_Screen_Clogged is Yes
      then Check includes 'screen unit clogged'

      if Symptom includes 'foul odour/black septic wastewater'
      and Check_Bar_Screen_Absent is Yes
      then Check includes 'screen unit absent'

      if Symptom includes 'foul odour/black septic wastewater'
      and Check_Decomposed_Wastewater is Yes
      then Check includes 'wastewater decomposed'

      if Symptom includes 'foul odour/black septic wastewater'
      and Check_Digester_Supernatant is Yes
      then Check includes 'digester supernatant'

      if Symptom includes 'foul odour/black septic wastewater'
      and Nature_of_Business is 'Municipal(domestic only)'
      and Check_Inadequate_Pretreatment is Yes
      then Check includes 'industrial load'

      if Symptom includes 'foul odour/black septic wastewater'
      and Nature_of_Business is 'Municipal(domestic+industrial)'
      and Check_Inadequate_Pretreatment is Yes
      then Check includes 'industrial load'

      if Symptom includes 'foul odour/black septic wastewater'
      and Nature_of_Business is 'Municipal(dom.+ind.+stormwater)'
      and Check_Inadequate_Pretreatment is Yes
      then Check includes 'industrial load'

      if Symptom includes 'foul odour/black septic wastewater'
      and Clarifier_Type is 'primary clarifier of a trickling filter'
      and Check_DO_Low is Yes
      then Check includes 'low DO in TF'

      if Symptom includes 'foul odour/black septic wastewater'
      and Clarifier_Type is 'secondary clarifier of a trickling filter'
      and Check_DO_Low is Yes
      then Check includes 'low DO in TF'

      if Symptom includes 'foul odour/black septic wastewater'
      and Clarifier_Type is 'primary clarifier of a trickling filter'
      and Check_Influent_Low is Yes
      then Check includes 'influent low'

      if Symptom includes 'foul odour/black septic wastewater'
      and Clarifier_Type is 'secondary clarifier of a trickling filter'
      and Check_Influent_Low is Yes
      then Check includes 'influent low'

      if Symptom includes 'foul odour/black septic wastewater'
      and Clarifier_Type is 'primary clarifier of a trickling filter'
      and Check_High_Biogrowth is Yes
      then Check includes 'high biogrowth'
```

```
if Symptom includes 'foul odour/black septic wastewater'
and Clarifier_Type is 'secondary clarifier of a trickling filter'
and Check_High_Biogrowth is Yes
then Check includes 'high biogrowth'

if Symptom includes 'foul odour/black septic wastewater'
and Clarifier_Type is
'primary clarifier of an activated sludge system'
and Check_RAS_Rate_Low is Yes
then Check includes 'low RAS'

if Symptom includes 'foul odour/black septic wastewater'
and Clarifier_Type is
'secondary clarifier of an activated sludge system'
and Check_RAS_Rate_Low is Yes
then Check includes 'low RAS'

if Symptom includes 'foul odour/black septic wastewater'
and Check_Drive_Power_Off is Yes
then Check includes 'collection system power switch off'


if Symptom includes 'foul odour/black septic wastewater'
and Clarifier_Type is
'primary clarifier of an activated sludge system'
and Check_Sludge_Pipe_Plugged is Yes
then Check includes 'pipe or sump plugged'

if Symptom includes 'foul odour/black septic wastewater'
and Clarifier_Type is
'secondary clarifier of an activated sludge system'
and Check_Sludge_Pipe_Plugged is Yes
then Check includes 'pipe or sump plugged'

if Symptom includes 'foul odour/black septic wastewater'
and Clarifier_Type is
'primary clarifier of an activated sludge system'
and Check_Sludge_Pump_Off is Yes
then Check includes 'sludge pump switch off'

if Symptom includes 'foul odour/black septic wastewater'
and Clarifier_Type is
'secondary clarifier of an activated sludge system'
and Check_Sludge_Pump_Off is Yes
then Check includes 'sludge pump switch off'

if Symptom includes 'foul odour/black septic wastewater'
and Clarifier_Type is
'primary clarifier of an activated sludge system'
and Check_Sludge_Pump_Fails is Yes
then Check includes 'pump fails'

if Symptom includes 'foul odour/black septic wastewater'
and Clarifier_Type is
'secondary clarifier of an activated sludge system'
and Check_Sludge_Pump_Fails is Yes
then Check includes 'pump fails'
```

```
    if Symptom includes 'foul odour/black septic wastewater'
    and Clarifier_Type is
    'primary clarifier of an activated sludge system'
    and Check_DO_Low is Yes
    then Check includes 'low DO'

    if Symptom includes 'foul odour/black septic wastewater'
    and Clarifier_Type is
    'secondary clarifier of an activated sludge system'
    and Check_DO_Low is Yes
    then Check includes 'low DO'

    if Symptom includes 'foul odour/black septic wastewater'
    and Clarifier_Type is
    'primary clarifier of a rotating biological contactor'
    and Check_DO_Low is Yes
    then Check includes 'low DO'

    if Symptom includes 'foul odour/black septic wastewater'
    and Clarifier_Type is
    'secondary clarifier of a rotating biological contactor'
    and Check_DO_Low is Yes
    then Check includes 'low DO'

    if Symptom includes 'foul odour/black septic wastewater'
    and Clarifier_Type is
    'primary clarifier of a rotating biological contactor'
    and Check_Organic_Overload is Yes
    then Check includes 'organic overload'

    if Symptom includes 'foul odour/black septic wastewater'
    and Clarifier_Type is
    'secondary clarifier of a rotating biological contactor'
    and Check_Organic_Overload is Yes
    then Check includes 'organic overload'




/****************************************************
/* ** Rules to Check for 'metal surfaces corroded'  **
/****************************************************

    if Symptom includes 'metal surfaces corroded'
    and Check_pH_Low is Yes
    then Check includes 'low pH'

    if Symptom includes 'metal surfaces corroded'
    and Check_Poor_Material is Yes
    then Check includes 'poor material'

    if Symptom includes 'metal surfaces corroded'
    and Check_Corrosive_Coagulant is Yes
    then Check includes 'corrosive coagulant'

/****************************************************
/* ** Rules to Check for 'sludge collector jerks/   *
/*                        jumps/stalls'             *
/****************************************************
```

```
      if Symptom includes 'sludge collector jerks/jumps/stalls'
      and Check_bad_socket is Yes
      then Check includes 'bad socket'

      if Symptom includes 'sludge collector jerks/jumps/stalls'
      and Check_Poor_Material is Yes
      then Check includes 'poor material'

      if Symptom includes 'sludge collector jerks/jumps/stalls'
      and Check_Chain_Link_Defect is Yes
      then Check includes 'chain link defective'

      if Symptom includes 'sludge collector jerks/jumps/stalls'
      and Check_Broken_Flight is Yes
      then Check includes 'flight broken'

      if Symptom includes 'sludge collector jerks/jumps/stalls'
      and Check_Deep_Sludge_Blanket is Yes
      then Check includes 'deep sludge blanket'

      if Symptom includes 'sludge collector jerks/jumps/stalls'
      and Check_Poor_Pretreatment is Yes
      then Check includes 'poor pretreatment'


/****************************************************
/* ** Rules to Check for 'broken scraper chain and   *
/*                        shear pin failure' ***     *
/****************************************************

      if Symptom includes 'broken scraper chain/shear pin failure'
      and Check_Wrong_Shear_Pin is Yes
      then Check includes 'wrong shear pin'

      if Symptom includes 'broken scraper chain/shear pin failure'
      and Check_Shear_Pin_Broke is Yes
      then Check includes 'shear pin broke'

      if Symptom includes 'broken scraper chain/shear pin failure'
      and Check_Poor_Flight_Align is Yes
      then Check includes 'poor flight alignment'

      if Symptom includes 'broken scraper chain/shear pin failure'
      and Check_Ice_Formed is Yes
      then Check includes 'ice formed'

      if Symptom includes 'broken scraper chain/shear pin failure'
      and Check_Sludge_Withdraw_Low is Yes
      and Check_Deep_Sludge_Blanket is Yes
      then Check includes 'deep sludge blanket'

/****************************************************
/* ** Rules to Check for 'noisy chain or chains      *
/*                        climb sprockets' ***       *
/****************************************************

      if Symptom includes 'noisy chain or chains climb sprockets'
      and Check_Drive_Unit_Misalign is Yes
```

```
      then Check includes 'drive unit misaligned'

      if Symptom includes 'noisy chain or chains climb sprockets'
      and Check_Drive_Parts_Worn is Yes
      then Check includes 'drive parts worn'

      if Symptom includes 'noisy chain or chains climb sprockets'
      and Check_Poor_Lubrication is Yes
      then Check includes 'poor lubrication'

      if Symptom includes 'noisy chain or chains climb sprockets'
      and Check_Excess_Rust is Yes
      then Check includes 'excess rust'

      if Symptom includes 'noisy chain or chains climb sprockets'
      and Check_Wrong_Chain_Size is Yes
      then Check includes 'wrong chain size'


/***************************************************
/* ** Rules to Check for 'excessive rake torque' *** *
/***************************************************

      if Symptom includes 'excessive rake torque'
      and Check_Scale_On_Rake is Yes
      then Check includes 'scale on rake'

      if Symptom includes 'excessive rake torque'
      and Check_Large_Solids is Yes
      then Check includes 'large solids'

      if Symptom includes 'excessive rake torque'
      and Check_Dosage_High is Yes
      then Check includes 'high dosage'

      if Symptom includes 'excessive rake torque'
      and Check_Poor_Torque_Design is Yes
      then Check includes 'poor torque design'

      if Symptom includes 'excessive rake torque'
      and Check_Wrong_Chain_Size is Yes
      then Check includes 'wrong chain size'


/***************************************************
/* ** Rules to Check for 'pumps or pipes plugged' ** *
/***************************************************

      if Symptom includes 'sludge pump or pipe fails/plugged'
      and Check_Large_Solids is Yes
      then Check includes 'large solids'

      if Symptom includes 'sludge pump or pipe fails/plugged'
      and Check_Large_Solids is Yes
      and Check_Bar_Screen_Absent is Yes
      then Check includes 'screen unit absent'

      if Symptom includes 'sludge pump or pipe fails/plugged'
      and Check_Large_Solids is Yes
```

```
     and Check_Screen_Unit_Damaged is Yes
     then Check includes 'screen unit damaged'

     if Symptom includes 'sludge pump or pipe fails/plugged'
     and Check_Sludge_Pump_Off is Yes
     then Check includes 'sludge pump switch off'

     if Symptom includes 'sludge pump or pipe fails/plugged'
     and Check_Sludge_Pump_Fail is Yes
     then Check includes 'sludge pump fails'



/**************************************************
/*                                                *
/*        Rules for finding 'Unlikely Causes'     *
/*                                                *
/**************************************************

     For all Cause1
     if   Check excludes check: of Cause1
     and  Likely_Cause includes Name: of Cause1
     then Unlikely_Cause includes Name: of Cause1


/**************************************************
/*                                                *
/*  Rules for finding Conclusive Causes, Remedies *
/*                    and Preventive Measures     *
/*                                                *
/**************************************************

seek Consultation

     For  all Cause1
     if   Likely_Cause includes Name: of Cause1
     and  Unlikely_Cause excludes Name: of Cause1
     then Conclusive_Cause includes Name: of Cause1;
          scan is done

     if   scan is done
     then run proc_unpack(number,Conclusive_Cause);
          unpack is done

     if   unpack is done
     and  number > 0
     then use screen2

     if   unpack is done
     and  number = 0
     then use screen1
```

```
/*************************************************************
/*
/*Rules for 'autocycle' or to run consultation again         *
/*                                                           *
/*************************************************************

      if   unpack is done
      and  restart is Yes
      then cycle_mode is autocycle;
           Consultation is completed

      if   unpack is done
      and  restart is No
      then cycle_mode is stop;
           Consultation is completed


/*    End of Rules for CLAR_EX.

/*    List of frames follow below:
```

1 :	Symptom	List
2 :	Wastewater_Type	List
3 :	Known_Pollutant	List
4 :	Chemical_Addition	List
5 :	declarations	Text
6 :	start	Text
7 :	screeno	Screen
8 :	Nature_of_Business	Text
9 :	Clarifier_Type	Text
10 :	Shape	Undefined
11 :	Inlet_Type	Undefined
12 :	Outlet_Type	Undefined
13 :	In_Tank_Baffle	Undefined
14 :	Sludge_Removal_Type	Text
15 :	startstep	Text
16 :	Cause1	Class
17 :	Symptom:	Slot referent Text
18 :	Likely_Cause	List
19 :	Name:	Slot referent Text
20 :	Poss_Cause_Float_Sludge	Screen
21 :	Poss_Cause_Bulk_Sludge	Screen
22 :	Poss_Cause_Solids_Loss	Screen
23 :	Poss_Cause_Small_Floc	Screen
24 :	Poss_Cause_Large_floc	Screen
25 :	Poss_Cause_Sludge_in_Hopper	Screen
26 :	Poss_Cause_High_Sludge_Blanket	Screen
27 :	Poss_Cause_Low_Underflow_Density	Screen
28 :	Poss_Cause_Shock_Influent_Load	Screen
29 :	Poss_Cause_Floating_Scum	Screen
30 :	Poss_Cause_Foam	Screen
31 :	Poss_Cause_Slime	Screen
32 :	Poss_Cause_Foul_Odour	Screen
33 :	Poss_Cause_AS_Foul_Odour	Screen
34 :	Poss_Cause_TF_Foul_Odour	Screen
35 :	Poss_Cause_RBC_Foul_Odour	Screen
36 :	Poss_Cause_Corrosion	Screen
37 :	Poss_Cause_Jerking_Collector	Screen
38 :	Poss_Cause_Switch_Trips	Screen
39 :	Poss_Cause_Broken_Chain	Screen
40 :	Poss_Cause_Noisy_Chain	Screen
41 :	Poss_Cause_Excess_Torque	Screen
42 :	Poss_Cause_Plugged_Pipes	Screen
43 :	Check_Collector_Fails	Text
44 :	Check	List
45 :	Check_Sludge_Withdraw_Low	Text
46 :	Check_Sludge_Pump_Fails	Text
47 :	Check_Sludge_Pipe_Plugged	Text
48 :	Check_Skimmer_Worn	Text
49 :	Check_Scraper_Worn	Text
50 :	Check_Oil_Presence	Text
51 :	Check_SVI_Out_Of_Range	Text
52 :	Check_Detent_Time_Long	Text
53 :	Check_RAS_Rate_High	Text
54 :	Check_DO_Low	Text
55 :	Check_FM_High	Text
56 :	Check_pH_Low	Text

57 :	Check_N_Conc_Low	Text
58 :	Check_Filamentous_Bacteria	Text
59 :	Check_Hyd_Overload	Text
60 :	Check_Feed_Rate_High	Text
61 :	Check_Feed_Rate_Low	Text
62 :	Check_Excess_Fines	Text
63 :	Check_RAS_Rate_Low	Text
64 :	Check_Influent_Toxic	Text
65 :	Check_Rake_Speed_Fast	Text
66 :	Check_Dosage_Low	Text
67 :	Check_Baffles_Misaligned	Text
68 :	Check_Paddle_Speed_Fast	Text
69 :	Check_Influent_Low	Text
70 :	Check_Rake_Speed_Slow	Text
71 :	Check_Dosage_High	Text
72 :	Check_Paddle_Speed_Slow	Text
73 :	Check_Grit_Rem_Malfunction	Text
74 :	Check_Grit_Rem_Absent	Text
75 :	Check_Rain_infiltration	Text
76 :	Check_Broken_Coll_Pipe	Text
77 :	Check_Clearing_Sewer	Text
78 :	Check_Toxic_Discharge	Text
79 :	Check_Grease_Trap_Wrong	Text
80 :	Check_Greasy_Influent	Text
81 :	Check_Scum_Trough_Blocked	Text
82 :	Check_Scum_Wiper_Worn	Text
83 :	Check_Skimmer_Not_Moving	Text
84 :	Check_Drive_Power_Off	Text
85 :	Check_Drive_Unit_Stalled	Text
86 :	Check_Surfactant	Text
87 :	Check_Polysaccharides	Text
88 :	Check_Over_Aeration	Text
89 :	Check_Solids_on_Weirs	Text
90 :	Check_AutoBrush_Malfunction	Text
91 :	Check_Bar_Screen_Clogged	Text
92 :	Check_Bar_Screen_Absent	Text
93 :	Check_Decomposed_Wastewater	Text
94 :	Check_Digester_Supernatant	Text
95 :	Check_Inadequate_Pretreatment	Text
96 :	Check_High_Biogrowth	Text
97 :	Check_Sludge_Pump_Off	Text
98 :	Check_Organic_Overload	Text
99 :	Check_Poor_Material	Text
100 :	Check_Corrosive_Coagulant	Text
101 :	Check_bad_socket	Text
102 :	Check_Chain_Link_Defect	Text
103 :	Check_Broken_Flight	Text
104 :	Check_Deep_Sludge_Blanket	Text
105 :	Check_Poor_Pretreatment	Text
106 :	Check_Wrong_Shear_Pin	Text
107 :	Check_Shear_Pin_Broke	Text
108 :	Check_Poor_Flight_Align	Text
109 :	Check_Ice_Formed	Text
110 :	Check_Drive_Unit_Misalign	Text
111 :	Check_Drive_Parts_Worn	Text
112 :	Check_Poor_Lubrication	Text

113	Check_Excess_Rust	Text
114	Check_Wrong_Chain_Size	Text
115	Check_Scale_On_Rake	Text
116	Check_Large_Solids	Text
117	Check_Poor_Torque_Design	Text
118	Check_Screen_Unit_Damaged	Text
119	Check_Sludge_Pump_Fail	Text
120	check:	Slot referent Text
121	Unlikely_Cause	List
122	Consultation	Text
123	Conclusive_Cause	List
124	scan	Text
125	proc_unpack	Procedure
126	number	Real
127	unpack	Text
128	screen2	Screen
129	screen1	Screen
130	restart	Text
131	cycle_mode	Text
132	shock_organic_load	Undefined
133	scraper_damaged	Undefined
134	skimmer_damaged	Undefined
135	collector_failure	Undefined
136	pump_failure	Undefined
137	pipe/sump_plugged	Undefined
138	oil	Undefined
139	SVI_out_of_range	Undefined
140	long_detention_time	Undefined
141	low_pH	Undefined
142	low_N2_conc	Undefined
143	high_F/M_ratio	Undefined
144	high_return_sludge	Undefined
145	low_return_sludge	Undefined
146	low_DO	Undefined
147	filamentous_bacteria	Undefined
148	high_influent	Undefined
149	low_influent	Undefined
150	feed_rate_set_low	Undefined
151	feed_rate_set_high	Undefined
152	low_chemical_dosage	Undefined
153	high_chemical_dosage	Undefined
154	low_sludge_removal	Undefined
155	excessive_fines	Undefined
156	excess_rake_speed	Undefined
157	low_rake_speed	Undefined
158	fast_paddle_speed	Undefined
159	slow_paddle_speed	Undefined
160	grit_remover_fails	Undefined
161	grit_remover_absent	Undefined
162	baffles_misaligned	Undefined
163	excess_stormwater	Undefined
164	pipe_broke	Undefined
165	clearance_of_sewer	Undefined
166	toxic_spill	Undefined
167	grease_trap_wrong	Undefined
168	high_grease_content	Undefined

169	: scum_trough_blocked	Undefined
170	: scum_wiper_damaged	Undefined
171	: skimmer_misaligned	Undefined
172	: no_power_supply	Undefined
173	: drive_unit_stalled	Undefined
174	: surfactant_present	Undefined
175	: high_polysaccharides	Undefined
176	: over_aeration	Undefined
177	: solids_on_weirs	Undefined
178	: autobrush_damaged	Undefined
179	: decomposed_flow	Undefined
180	: screen_unit_clogged	Undefined
181	: screen_unit_absent	Undefined
182	: screen_unit_damaged	Undefined
183	: industrial_load	Undefined
184	: digester_supernatant	Undefined
185	: high_bio_grow_in_TF	Undefined
186	: low_DO_in_TF	Undefined
187	: collect_system_off	Undefined
188	: sludge_pump_off	Undefined
189	: high_organic_load	Undefined
190	: poor_material_used	Undefined
191	: corrosive_coagulant	Undefined
192	: bad_socket	Undefined
193	: defective_chain_link	Undefined
194	: broken_flight	Undefined
195	: deep_sludge_blanket	Undefined
196	: poor_pretreatment	Undefined
197	: wrong_shear_pin_size	Undefined
198	: shear_pin_broke	Undefined
199	: flight_misaligned	Undefined
200	: ice_formed	Undefined
201	: drive_unit_misalign	Undefined
202	: moving_parts_worn	Undefined
203	: poor_lubrication	Undefined
204	: excess_rust	Undefined
205	: wrong_chain_size	Undefined
206	: scale_on_rake	Undefined
207	: large_solids_in_flow	Undefined
208	: poor_torque_design	Undefined
209	: option1	Text
210	: option2	Text
211	: option3	Text
212	: option4	Text
213	: option5	Text
214	: option6	Text
215	: option7	Text
216	: option8	Text
217	: option9	Text
218	: option10	Text
219	: option11	Text
220	: option12	Text
221	: option13	Text
222	: option14	Text
223	: option15	Text
224	: option16	Text
225	: option17	Text
226	: option18	Text
227	: option19	Text
228	: option20	Text
229	: cycle_counter	Real

APPENDIX C

GLOSSARY OF TERMS USED IN CLAR_NET

GLOSSARY OF TERMS USED IN CLAR_NET

1.	"AccuSludge"	=	Sludge accumulated at the bottom of the clarifier.
2.	"Aeration"	=	Aeration rate of aerators; a rate higher or lower than that required could result in excess or deficient dissolved oxygen.
3.	"Agitation"	=	Agitation of aerators in the aeration basin.
4.	"BOD"	=	Biological Oxygen Demand, as a measure of the oxygen amount needed by the microorganisms.
5.	"Baffle"	=	The condition of the baffles in clarifier, either damaged, worn or inadequate.
6.	"Bulking"	=	Bulking as a symptom in clarifier. It appears as clouds of billowing sludge that occur in secondary clarifier when the sludge becomes too light and will not settle properly
7.	"CNPRatio"	=	The C:N:P ratio (Carbon:Nitrogen:Phosphorus) needed as nutrient to the microorganisms.
8.	"DO"	=	Dissolved oxygen in the wastewater
9.	"Defloc"	=	Deflocculation
10.	"Denitrify"	=	Denitrification. The removal of Nitrogen or Nitrogen compound from waste water.
11.	"DetentTime"	=	The detention time of the waste water.
12.	"DispGrowth"	=	Dispersed growth of microorganisms in wastewater.
13.	"Effl_Ammonia"	=	The amount of ammonia in the effluent from the secondary clarifier.
14.	"Effl_BOD"	=	The amount of Biochemical Oxygen Demand in the effluent from the secondary clarifier.
15.	"Effl_Nitrate"	=	The amount of nitrate in the effluent from the secondary clarifier.
16.	"ExcessFoam"	=	Excess foam on the surface of the clarifier

17. "FMRatio" = F/M Ratio or Food/Microorganism ratio. It is a measure of food provided to microorganism in an activated sludge system.

18. "FilBact_A" = Filamentous Bacteria type A. Organisms that grow in a thread or filamentous form and cause bulking. Common types are thiothrix and actinomycetes.

19. "FilBact_B" = This type of filamentous bacteria does not cause bulking, denoted type B in CLAR_NET for easy separation from the bulking-causing bacteria (denoted as Filbact_A)

20. "FloatSludge" = Sludge that floats on the surface of clarifier.

21. "Hydload" = Hydraulic load. Hydraulic loading refers to the flow (m^3/day) to the aeration basin and clarifier. Hydraulic overload means excess flow to these units.

22. "InaFloatable" = Inanimate floatables that appear on the water surface of the clarifier

23. "InfluentType" = The type of influent, either only industrial wastewater, or domestic wastewater, or both.

24. "MassSettRate" = The rate at which the suspended solids settle to the bottom of the clarifier.

25. "Mousse" = Mousse-like condition on the water surface of clarifier.

26. "N_Load" = The amount of Nitrogen as nutrient feed to the wastewater treatment system.

27. "Norcardia" = A type of microorganism in waste water that is known to cause foam.

28. "NonFloc" = Suspended solids that are not flocculated.

29. "Oil" = Presence of oil on the waste water of the clarifier

30. "OrganicLoad" = Organic load of the wastewater treatment system

31. "Outlet" = The condition of the sludge outlets or ports; whether they are in good operation, or blocked.

32. "P_Load" = The amount of Phosphorus as nutrient feed to the wastewater treatment system.

33. "PinFloc" = Pin floc which is usually less than 0.76mm in diameter, and is observed suspended throughout moderately turbid secondary clarifier.

34. "Pretreatment" = The condition of pretreatment of influent wastewater into the aeration basin and the secondary clarifier. This may include poor neutralization, inadequate oil removal in the oil-water separator, poor screening to remove sand and large objects.

35. "PumpingRate" = Sludge withdrawal pumping rate

36. "RASRate" = Return activated sludge rate

37. "RisingSludge" = Sludge rising to the water surface of the clarifier

38. "Scraper" = The condition of the scraper. The scraper is located at the bottom of the clarifier (or sedimentation basin) and its function is to scrap the sludge to the collection point.

39. "SepticSludge" = Septic sludge. It is a condition where generally sludge turns darker in colour, contains little or no dissolved oxygen and creates a heavy oxygen demand.

40. "ShortCircuit" = Short-circuiting of flow in clarifier

41. "SludgeAccuRt" = The rate of accumulation of sludge

42. "SludgeAge" = Sludge age, which is considered as the average floc age of sludge in the activated sludge system.

Sludge age (day) = (kg of activated sludge in system)/(kg sludge withdrawn per day + kg sludge lost in effluent)

43. "SludgeConct" = The concentration of sludge at the bottom of the clarifier.

44. "SolidOvrWeir" = Solids flow over the weirs of clarifier

45. "Spill" = Accidental spill of chemicals or any liquid

46. "Surfactant" = Abbreviation for surface-active agent. The active agent in detergent that possesses a high cleaning ability.

47. "ToxicWaste" = Toxic discharge into the wastewater treatment system, such as acid, concentrated alkali.

48. "TurbidSusp" = Turbid suspension

49. "TurbidWaste" = Turbid waste such as clay

50. "VolSldgAbsRt" = Volume Sludge Abstract Rate, this is the rate at which sludge is being wasted from the treatment system, also known as waste activated sludge rate.

51. "Weir" = The level of weirs, whether is level or not.

52. "pH" = pH of the influent to the wastewater treatment system.

APPENDIX D

TRANSCRIPTS OF INTERVIEWS WITH DOMAIN EXPERTS

TRANSCRIPTS OF INTERVIEWS WITH DOMAIN EXPERTS
(Summary of key points elicited)

1. Q. Please explain the "nitrification" process as known to occur in biological wastewater treatment system.

   A. In an activated sludge wastewater treatment system, nitrification process simply means converting the wastewater containing toxic ammonia (such as those from domestic wastewater) to nitrite and nitrate:

   The nitrification would involve 2 types of bacteria:

   a. Nitrosomonas: oxidizes Ammonia to Nitrite

$$2NH_4^+ + 3O_2 = 2NO_2^- + 4H^+ + 2H_2O$$

   b. Nitrobacter: oxidizes Nitrite to Nitrate

$$2NO_2^- + O_2 = 2NO_3^-$$

2. Q. What about "denitrification"?

   A. Denitrification Process: The Nitrates resulted from nitrification process is then converted to the Nitrogen gas through a reduction process. There are several types of bacteria that can cause denitrification, the most common type is generally known as Pseudomonas.

   Excess Nitrogen gas bubbles released during the activated sludge process may attach to the settled sludge, so making these sludge "lighter" and subsequently they float on the water surface of the clarifier. This is what commonly observed as "floating sludge" on clarifier.

3. Q: What then causes excess Nitrates and excess Ammonia in the effluent?

   A: Excess Nitrate can be caused by poor denitrification. Since Nitrate should be reduced to Nitrogen gas during denitrification, excess Nitrate means the denitrification is not adequate to convert all Nitrate into Nitrogen.

   On the other hand, excess Ammonia in the effluent could be caused by poor nitrification. Poor nitrification is mainly caused by low dissolved oxygen and pH values outside the neutral zone, that is, above 9 or below 6. Another factor which may contribute to poor nitrification is the presence of inhibitors, such as metals - Nickel, Chromium and Copper.

4. Q. What does "sludge bulking" mean to you?

A. "Sludge bulking" simply refers to sludge that is difficult to settle. Usually, the sludge solid usually occupy too much volume after the liquor has settled for a normal period of time. Bulking could be caused by a number of factors, but bulking itself is known to be caused by the presence of filamentous bacteria. That is why people specifically called this filamentous bulking. Under a microscope, filamentous bacteria is recognized as hair-like bacteria.

Sludge bulking could also be caused by other reasons, some of them are: shock loading, poor aeration, nutrient imbalance, too low sludge age and generally poor operating conditions.

5. Q. What causes excess foam on the surface of the clarifier?

A. Generally, I attribute that mainly to the presence of Nocardia, a microorganism in the wastewater. We have been treating wastewater for over 30 years in this treatment plant, and our research showed that Nocardia is the main cause of the problem. The paper on Nocardia described this problem in detail. The factor known factor is the presence of surfactant.

6 Q. In your best estimate, what is the percentage of excess foam is caused by Nocardia as compared to that caused by surfactant?

A. I would say about 80 percent of the time, the cause is Nocardia, and only about 20% is surfactant.

7. Q. It is generally known that septic sludge is due to the poor dissolved oxygen (D.O.) level in the wastewater. What other factors also cause the sludge to be septic?

A. There are other factors besides low D.O. level in the wastewater. A faulty scraper or scraper that malfunctions may not move the sludge to the draw-off hopper, leaving a thick sludge and could cause septicity. Besides, if the sludge wastage rate is low (as"VolSldgAbsRt" in the network), then the "old" sludge will return or remain in the system, which will cause the sludge to turn septic also. Other factor such as excessive organic load in the influent could also contribute to the problem.

8. Q. From all the wastewater treatment plants that you have supervised and known, roughly what percentage of the activated sludge is recirculated, and what percentage is wasted?

A. This would have to vary from plant to plant. From my experience, I would say about 85% of the sludge is recirculated and the rest of 15% is wasted.

9. Q. Could you explain "deflocculation" in activated sludge system and how does that affect the overall treatment operation?

A. As the name implies, "deflocculation" refers to no flocculation, or simply means the sludge breaks up into tiny particles which settle poorly and the effluent becomes very "muddy" or turbid. Deflocculation may occur because of toxic wastes, acid waste, anaerobic condition in the mixed liquor, overloading of the aeration tank, and/or excess agitation due to turbulence of aerators. The main causes are: toxic waste, pH and excessive agitation.

10. Q. What then would you call a turbid suspension as " pin floc"?

A. According to the literature, pin flocs are usually about the size of less than 0.03 in (0.76 mm) in diameter and they are observed suspended throughout the whole clarifier. They may be caused by excessive agitation in aerators, sludge age too old, low dissolved oxygen level, and low nutrient supply.

11. Q. How is "F/M Ratio" related in an activated sludge system?

A. In biological wastewater treatment, "F/M Ratio" refers to food to microorganism ratio. It is a measure of food provided to the microorganism or bacteria in the aeration basin.

In mathematical form, F/M ratio is defined as:

$$\frac{\text{Food}}{\text{Microorganism}} = \frac{\text{BOD (kg/day)}}{\text{MLSS (kg)}}$$

12. Q. Please explain further the above equation.

A. BOD is biological oxygen demand which can be explained as the rate at which microorganisms use the oxygen in wastewater while stabilizing decomposable organic matter under aerobic conditions. During the decomposition process, organic matter serves as food for bacteria and energy results from its oxidation. So, the higher BOD in the wastewater, the higher is the F/M ratio. MLSS refers to the suspended solids in the mixed liquor of an aeration tank.

13. Q. Talking about microorganisms, in order to make them survive well in the mixed liquor, I believe the influent should have sufficient nutrient and must not be toxic at all. So, to what degree does toxicity affect the operation?

A. Toxicity causes a severe slowdown or death of working bacteria and could easily cause upsets in the treatment system. Toxic waste could originate from uncontrolled spills or industrial discharges that contain heavy metals, acids, insecticides, or pesticides. As mentioned earlier, deflocculation is one of the effects of the presence of toxic substance.

14. Q. Rising sludge is known to be another major operational problem in wastewater treatment. Could you elaborate more on this problem?

A. A lot of people confuse "rising sludge" to "bulking". For rising sludge, the sludge settles and compacts satisfactorily on the bottom of the clarifier, but after settling, it rises to the top of the secondary clarifier in small particles, each about the size of a pea.

Rising sludge is caused by denitrification or septicity. Presence of oil could also cause the sludge to be lighter and the sludge to rise to the surface.

15. Q. What do you think are the operational strategies for clarifiers?

A. Influent flow is said to be most common factor influencing clarifier performance . Both the surface loading and detention time of the wastewater are directly related to flow. In most treatment plants, the surface loading and detention time vary widely throughout the day as a result of varying flows from activities of people and industries. Despite of the varying flows, most clarifiers are able to remove BOD and suspended solids consistently.

Most clarifiers that do not produce an acceptable effluent are mainly due to operator errors or equipment problems.

The best strategy for a clarifier is to develop and implement a good preventive maintenance program, and to closely monitor operating conditions, and to respond to any lab results that indicate imminent operational problem. Any other clarifier problems result from abnormal conditions.

16. Q. Could you elaborate some abnormal operating conditions in clarifiers?

A. To me, abnormal conditions that could affect clarifier performance are caused by the following:

i) toxic wastes from industrial spills
ii) hydraulic overload
iii) septicity of sludge

These conditions usually cause the clarifier problems, as the operator may have insufficient time to deal with them before the problems occur.

17. Q. There are a few factors that could cause settling problem in clarifiers, and one of them is "short-circuiting". Please explain.

A. As wastewater enters the clarifier, it should be evenly dispersed across the entire tank with the same velocity in all areas toward the discharge end. When the velocity is greater in some sections than in others, serious short-circuiting may occur.

The high velocity may decrease the detention time in that area, and particles may be held in suspension and pass through the discharge end of the tank without having sufficient time to settle. On the other hand, if the velocity is too low, undesirable septic conditions may occur. Short-circuit may be caused by uneven weir plates or missing baffles.

18. Q. Let's discuss about the probabilities of some of the clarifier problems occurring. What do you think for most of the well operated system, what is the probability that a deviation outside the norm would occur? For instance, what is the probability that the baffles would be in good condition versus probability of being in faulty condition? What is the probability that pH system is in good condition, etc.?

A. To my best estimate, for a normally well-run treatment system, meaning the maintenance is very good and the operators are the probability of having good operating condition is very high. This means the chances of having good pH level, baffle condition, weir plate condition, pretreatment condition, aeration rates, etc. are very high. I would put it as at least 95 to 99% of the time.

APPENDIX E

QUESTIONNAIRE FOR DOMAIN EXPERTS

QUESTIONS FOR WASTEWATER TREATMENT SUPERVISORS

Note: Except for the information given in each question, all other conditions in the activated sludge system are assumed to work well or normally.

Score 1 - 100, 1=least likely to happen, 100=most likely.

1. If: DO in the mixed liquor is low
   Q: What is the probability of:
   occurrence of Septic Sludge? ______

2. If: DO in the mixed liquor is low
   Q: What is the probability of:
   occurence of dispersed growth? ______

3. If: sludge outlet pipe is blocked
   Q: What is the probability of:
   occurence of septic sludge? ______

4. If: DO is low and sludge outlet pipe is blocked
   Q: What is the probability of:
   occurence of septic sludge? ______

5. If: toxic spill occurs,
   Q: What is the probability of:
   deflocculation ______

6. If: toxic spill occurs, pH is very low (acidic), and aeration on the mixed liquor is high
   Q: What is the probability of:
   deflocculation? ______

7. If: toxic spill occurs, and organic load is normal
   Q: What is the probability of:
   effluent BOD is high? ______

8. If: toxic spill occurs, and organic Load is high
Q: What is the probability of:
effluent BOD is high? ____________

9. If: there is excessive solids flowing over the weirs and toxic waste is present
Q: What is the probability of:
effluent BOD is high? ____________

10. If: sludge age is high
Q: What is the probability of:
presence of pin floc? ____________

11. If: influent type is industrial waste only
Q: What is the probability of:
effluent BOD is high? ____________

12. If: nutrient is deficient in nitrogen and DO is low
Q: What is the probability of:
presence of filamentous bacteria (A)? _____

13. If: scraper malfunctions
Q: What is the probability of:
no excessive solids flowing over weir?_____

14. If: return activated sludge (RAS) rate is low
Q: What is the probability of:
absence of bulking? __________

15. If: RAS rate is normal and F/M ratio is high
Q: What is the probability of:
absence of bulking? ____________

16. If: RAS rate is low and F/M ratio is high
Q: What is the probability of:
absence of bulking? ________

17. If: turbidity is observed on the water of clarifier
Q: What is the probability of:
occurence of pin floc? ________

18. If: hydraulic load is high
Q: What is the probability of:
having low detention time? ________

19. If: excess foam is observed
Q: What is the probability of:
presence of Nocardia? ________

20. If: solids flowing over the weirs is excessive
Q: What is the probability of:
outlet pipe is blocked? ________

21. If: solids flowing over the weirs is excessive
Q: What is the probability of:
effluent BOD is high? ________

22. If: solids flowing over the weirs is excessive
Q: What is the probability of:
weir is not level? ________

23. If: solids flowing over the weirs is excessive
and BOD in the effluent is high
Q: What is the probability of:
presence of toxic waste in the influent? ________

24. If: bulking occurs

Q: What is the probability of:

F/M ratio is high? ___________

25. If: Nitrate in the effluent is high

Q: What is the probability of:

denitrification occurs? ________

26. If: the Ammonia in the effluent is high

Q: What is the probability of:

pH of influent is too alkali? _________

27. If: floating sludge occurs

Q: What is the probability of:

DO is low? ___________

28. If: oil is observed on the surface of clarifier

Q: What is the probability of:

poor pretreatment? ________

29. If: sludge concentration at the clarifier bottom is very thick

Q: What is the probability of:

low volume sludge abstraction rate? _______

30. If: pin floc occurs

Q: What is the probability of:

excessive agitation by aerators? ________

APPENDIX F

PROOF OF EQUIVALENCE

To Prove: That the joint probability distribution P(A.B.C.D.E.F.G.H) derived from the dependencies defined in the DAG in Figure 4.1 as given by the equation 4a:

$$P(A,B,..H)=P(H|D,E)P(G|E)P(F|D)P(E|B,C)P(D|A)P(C|A)P(B)P(A) \tag{4a}$$

is identical to that derived from the triangulated graph by dividing the product of joint distributions on the cliques (C1 to C6) by the product of the joint distributions on their intersections, as defined by equation 4b as:

$$P(A,B,\dots H)=\frac{P(A,C,D)P(C,D,E)P(B,C,E)P(D,E,H)P(D,F)P(E,G)}{P(C,D)P(E,C)P(E,D)P(D)P(E)} \tag{4b}$$

Proof:(from unpublished work by Walley (1996))