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Dynamic Failure Risk Assessment of Wastewater Treatment And Reclamation Plant Using Dynamic Bayesian Network

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ABSTRACT: *Due to the growing scarcity of water resources, wastewater reuse has become one of the most effective solutions for industrial consumption. However, various factors can detrimentally affect the performance of a wastewater treatment plant (WWTP), which is considered a risk of not fulfilling the effluent requirements. Thus, to ensure the quality of treated wastewater, it is essential to analyse system failure causes and their potential outcomes and mitigation measures through a systematic dynamic risk assessment approach. In the project Dynamic Bayesian network (DBN) can be effectively used in this context. Like the conventional Bayesian network (BN), the DBN can capture complex interactions between failure contributory factors. Additionally, it can forecast the upcoming failure likelihood using a prediction inference. This proposed methodology is used applied to a any WWTP. Generally, Past failure data is used to develop the DBN model and to identify the crucial risk factors that are further used to reduce the risk in the upcoming period. Applying the proposed risk mitigation measures can decrease the failure risk significantly reduced. The proposed model showed the capability of the DBN in risk management of a WWTP system which can help WWTPs' managers and operators achieve better*
performance for higher reclaimed water quality.

Keywords: WWTP,DBN,BN.

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I. INTRODUCTION:

People's lives have been changed dramatically due to technological advancement in smart and diverse types of consumer electronics. These devices, known as the Internet of Things (IoT), are connected by advanced communication technologies to the Internet to exchange information People's lives have been changed dramatically due to technological advancement in smart and diverse types of consumer electronics. These devices, known as the Internet of Things (IoT), are connected by advanced communication technologies to the Internet to exchange information People's lives have been changed dramatically due to technological advancement in smart and diverse types of consumer electronics. These devices, known as the Internet of Things (IoT), are connected by advanced communication technologies to the Internet to exchange information

It's crucial to investigate system failure causes, potential consequences, and mitigation strategies using a systematic dynamic risk assessment technique in order to ensure the quality of treated wastewater. This work demonstrates how a dynamic Bayesian network (DBN) can be applied successfully in this situation. Reclamation plant refers to a collection of apparatuses, buildings, machinery, systems, and management techniques that generate recovered water that is adequate for the intended usage. A dynamic Bayesian network (DBN) is a Bayesian network (BN) that connects variables over subsequent time steps. Three variables make up a dynamic Bayesian network. A three-step Bayesian network was built. Dynamic Bayesian Network in its simplest form. Degraded performance in a WWTP is a risk associated with failing to meet the effluent standards for reuse due to a variety of circumstances. As a result, it is crucial to assess various failure scenarios and how they affect a WWTP using a methodical risk-based approach. An industrial WWTP is subject to significant risk factors, which can be divided into four categories: equipment failures, human errors, design flaws, and wet weather conditions. Static models are insufficient for risk analysis due to the numerous components, varied dynamic performances, and operational issues that a WWTP encounters. Water and wastewater treatment plants use fault tree analysis (FTA), bow-tie analysis (BT), and Bayesian networks (BN) for risk assessment. With the ability to handle complex WWTPs in industrial applications, the VIP-DBN offers a more useful way for soft sensor modeling and a guarantee for the efficient decision-making of wastewater treatment processes for papermaking businesses [1]. In this paper to enhance the modeling capability in WWTPs, a fuzzy partial least squares-based dynamic Bayesian network (FPLS-DBN) is suggested [2]. The process of choosing an effective wastewater treatment system is complicated by technical, economic, regulatory, environmental, social, and political issues. Although this issue has already been addressed through the dimensioning approach, our research proposal established a continuous discrete, non-parametric Bayesian network decision-making model for traditional secondary treatment of municipal wastewater [3]. The wastewater treatment system based on the Modified Sequencing Batch Reactor (MSBR) was modeled and predicted using a Bayesian network-based technique in this study [4]. With the ability to handle complex WWTPs in industrial applications, the VIP-DBN offers a better practical technique for soft sensor modeling and a guarantee for the efficient decision-making of wastewater treatment processes for papermaking firms [5]. This paper uses the modified sequencing batch reactor (MSBR) as an analysis object. Using the MSBR's influent water quality, operational status, and effluent effect data, a BN model was built, and a novel method based on BN is then suggested to analyze the influencing factors of the wastewater treatment system[6].

II. Dynamic bayesian networks

Our focus will be on BNs and their expansions that attempt to combine uncertainty and temporal dimension. Beginning with fundamental ideas, we move on to more complex ideas before introducing static Bayesian networks and the fundamentals of dynamic Bayesian networks as potent representational tools for such uncertain events. There are various stages in the creation of DBNs. Following that, we review a number of dynamic models, discuss several practical computing methods for them, and list common issues that can occur during these computations. In an effort to model events that have both temporal and environmental aspects, Bayesian networks (BNs) introduced a novel methodology (time-series modelling). A Dynamic Bayesian Network (DBN) is the name of this innovative time-series modeling tool. It was also demonstrated that effective HMMs are merely a particular instance of dynamic Bayesian networks.

- **BN Terminology:**

A specific method for using probability to solve statistical problems is known as Bayesian statistics. In light of additional information or supporting evidence concerning random events, it gives us the mathematical skills to revise our ideas about those events. In order to make definitions understandable to people with less education, they are condensed and offered in a descriptive form rather than an exact axiomatic one.

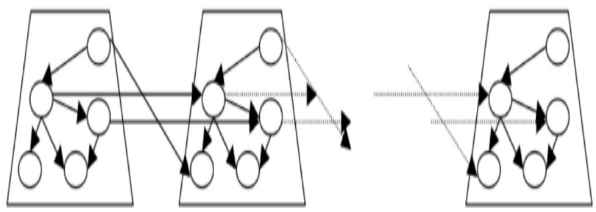
- **BN Inference:**

The ability to infer conditional connections between variables by looking at the network's graph is an important feature of Bayesian networks. As a result, the set of BN nodes can be divided into non-overlapping subgroups of conditionally independent nodes. When performing the probability inference, this decomposition is crucial. The task of determining a node's probability for each state in a Bayesian network when other variables are known is known as inference.

- **Dynamic Bayesian Networks:**

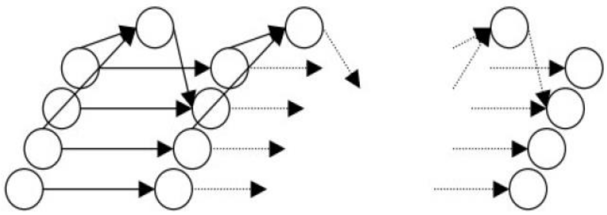
A model that portrays a system that is dynamically changing or growing through time should be called Dynamic Belief Networks (DBN). Users will be able to monitor and change the system throughout time, and even forecast how it will behave going forward, thanks to this model. In these concepts, a "motive force" is associated with the word "dynamic." The static BN's transformation into a model of "motive forces" might be seen as its conversion into a dynamic model.

- **Time slice:**



Using a time slice to represent a moment in time in a developing temporal process. The belief network, or "time slice," can be described as a collection of sub-models, each of which represents the system at a distinct point in time. Temporal relations, which are depicted by arcs connecting certain variables from two subsequent time slices, connect these time slices together.

- **Over Temporal model:**



Where each time slice in the network has copies of the same sub-models. It therefore shares the same temporal structure as the earlier model. However, within a time slice, linkages between state variables are not permitted.

- **Static BN:**

DBNs we may be interested in the following:.

1.Inference: estimate the pdf of unknown states given some known observations, and initial probability distribution.

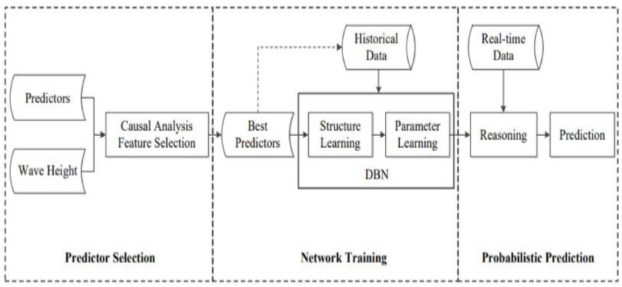
2. Decoding: find the best-fitting probability values for sequence of hidden states that have generated the known sequence of observations.

3. Learning: given a number of sequences of observations, estimate parameters of a DBN such that they best fit to the observed data, and make the best model for the system.

4. Pruning: distinguishing which nodes are semantically important for inference in DBN structure, and which are not, and removing them from the network.

- **DBN-IF :**

The main goal of IF theory is to use causal analysis to choose the most effective set of predictive variables for DBN. Structure learning and parameter learning are used to build DBN for probabilistic prediction. Next, we'll demonstrate how DBN can handle uncertainty to provide strong predictions from network learning and how IF can screen the top predictors. In order to create a probabilistic prediction model, DBN and IF are integrated.



- **Accident reports, records:**

The specifics of a car collision are documented in an accident report. When submitting a claim to an insurance provider, crash reports are a crucial component. A copy of the report could be used to establish liability for the collision and determine who would foot the bill for any required repairs, property damage, or medical expenses.

- **Testing structures for integrity prior:**

An approach to determine if a structure is prepared to resist operating circumstances safely and reliably for the duration of its anticipated lifetime is known as structural integrity assessment.

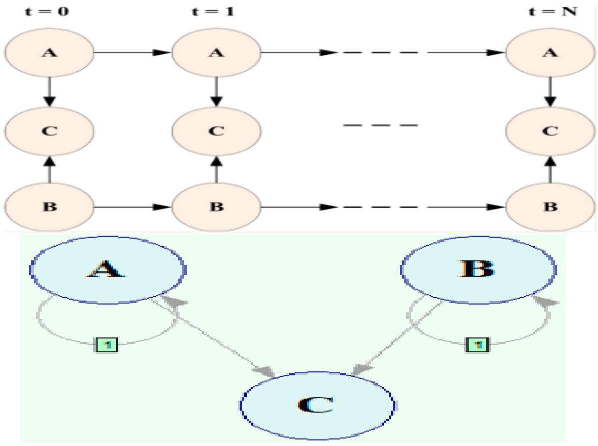
II. Assessment of Wastewater Treatment and Reclamation

This chapter's goal is to discuss the main wastewater treatment methods currently in use. In the end, the technology chosen as suitable for one application might not be the best for another. Based on site-specific elements such available resources, climate, land availability, economics, etc., selection will be made. The failure risk of a waste water treatment facility can be effectively decreased in this situation by using a dynamic Bayesian network (DBN).

- **DBN for wastewater Treatment Plant:**

Like the traditional BN, DBN also employs nodes to represent variables in a graph. Additionally, the arcs indicate dynamic causal connections between the variables. Additionally, some nodes might not change over time and should not be expressed dynamically. Based on the analysis of PFDs and expert knowledge, a conceptual model and the causal connections between the nodes are developed.

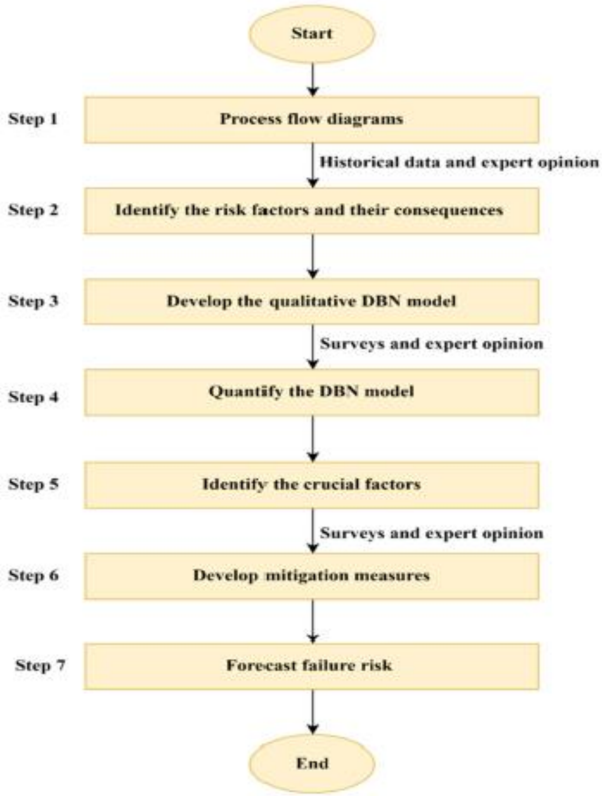
$$P(F_t/F_{t-1})=\Pi_{i=1}^{n}P(F_{i,t}/Pa(F_{i,t}))$$



- **CPT:**

Time dependency must be included in the CPTs since variables depend on the previous time slice. Additionally, two sets of CPTs are needed to describe a dynamic node. The second set gives the result of dynamic variation. A DBN has two notable features: smoothing and prediction inferences.

$$P(F_{1:N})=\prod_{t=1}^{N}\prod_{i=1}^{n}P(F_{i,t}/Pa(F_{i,t}))$$



Three scenarios are selected for leaf node.
1. Without the fouling, corrosion, scale and bio film in the facilities of an industry (C1)
2. Long-term creation of the fouling, corrosion, scale and bio film in the industrial facilities (C2)
3. Short-term and severe creation the fouling, corrosion, scale and bio film in the industrial facilities (C3).

The risk is the summation of C2 and C3 probabilities, while the C1 probability equals the reliability.

III. CONCLUSION

A dynamic risk assessment of the system may be an effective technique to spot and minimize failures given the numerous risks and uncertainties that can arise during a WWTP's operational term. With the purpose of capturing complex interplay among failure variables, uncertainty, multistate analysis, and modeling dynamic risk and reliability, the current study carried out an industrial WWTP risk assessment utilizing a systematic DBN-based technique.

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