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Enhancing Control Room Operator Decision Making: An Application of Dynamic Influence Diagrams in Formaldehyde Manufacturing

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Abstract. In today's rapidly evolving industrial landscape, control room operators must grapple with an ever-growing array of tasks and responsibilities. One major challenge facing these operators is the potential for task overload, which can lead to decision fatigue and increased reliance on cognitive biases. To address this issue, we propose the use of dynamic influence diagrams (DID) as the core of our decision support system. By monitoring the process over time and identifying anomalies, DIDs can recommend the most effective course of action based on a probabilistic assessment of future outcomes. Instead of letting the operator choose or search for the right procedure, we display automatically the optimal procedure according to the model. The procedure is streamlined compared to the traditional approach, focusing on essential steps and adapting to the system's current state. Our research tests the effectiveness of this approach using a simulated formaldehyde production environment. Preliminary results demonstrate the ability of DIDs to effectively support control room operators in making informed decisions during times of high stress or uncertainty. This work represents an important step forward in the development of intelligent decision support systems for the process industries.

Keywords: Dynamic influence diagram · Decision support · Process industry · Workload · Situation awareness.

1 Introduction

Modern control room environments present unique challenges to operators who must effectively manage complex processes in real-time. These challenges include task overload, uncertain decision-making situations, and the pressure to meet competing demands, all of which contribute to operator fatigue. Addressing these challenges necessitates innovative solutions that enhance operator resilience and support improved decision-making. In a previous study [3], Bayesian networks were employed as decision support tools and anomaly detectors, offering the advantage of constructing a reliable model for optimal decision-making. By utilizing dynamic Bayesian networks (DBN) [1] the process can be continuously monitored over time. Another study [4] extensively describes the use of DBNs for fault diagnosis and event prediction in the industry. Additionally, influence diagrams [1], which are based on the Bayesian network framework, have been widely studied to be an effective decision-support tool in industrial settings [5]. A promising approach in this regard is the application of dynamic influence diagrams (DID) as the core component of a decision support system.

This paper aims to contribute to the understanding of the application of DID in industry contexts, specifically focusing on its utilization in formaldehyde production management to enhance control room operator decision-making. Utilizing a high-fidelity simulation test, we evaluate the impact of DID on reducing operator workload and improving situational awareness when facing abnormal events. The paper begins with section 2 by providing background information on dynamic influence diagrams, followed by a detailed examination of the case study and the model construction process in section 3. In section 4 we assess the model's performance in a preliminary study and discuss its limitations. Section 5 concludes the paper.

2 Methodology

In this section, we introduce the dynamic influence diagram framework that will be used to build the decision support system.

2.1 Influence diagram

An influence diagram is a graphical representation that depicts the relationships between variables in a decision problem [1]. It is a variant of a Bayesian network that incorporates decision nodes, chance nodes, and utility nodes to facilitate decision-making under uncertainty. Decision nodes represent choices or actions that can be taken, chance nodes represent uncertain events or states of the world, and utility nodes represent the preferences or values associated with different outcomes. Influence diagrams provide a structured framework for modeling and analyzing complex decision problems, allowing decision-makers to assess the expected utility of different choices and make informed decisions. A limited memory influence diagram is used to relax the perfect recall of the past and the total order of the decisions assumptions (see [1]). We define the discrete limited memory influence diagram as follows:

Definition 1. *(Discrete Influence Diagram) [1] A (discrete) influence diagram $N = (X, G, P, U)$ consists of:*

- *A DAG $G = (V, E)$ with nodes V and directed links E encoding dependence relations and information precedence.*
- *A set of discrete random variables X_C and discrete decision variables X_D, such that $X = X_D \cup X_C$ represented by nodes of G.*

- *A set of conditional probability distributions P containing one distribution $P(X_v|X_{pa(v)})$ for each discrete random variable X_v given its parents $X_{pa(v)}$.*
- *A set of utility functions U containing one utility function $u(X_{pa(v)})$ for each node v in the subset $V_U \subseteq V$ of utility nodes.*

To identify the decision option with the highest expected utility, we compute the expected utility of each decision alternative. If A is a decision variable with options $a_1, \ldots, a_m$, H is a hypothesis with states $h_1, \ldots, h_n$, and ϵ is a set of observations in the form of evidence, then we can compute the probability of each outcome of the hypothesis h_j and the expected utility of each action a_i. The utility of an outcome (a_i, h_j) is $U(a_i, h_j)$ where $U(\cdot)$ is our utility function. The expected utility of performing action a_i is

$$EU(a_i) = \sum_{j=1}^{n} U(a_i, h_j)\, P(h_j|\epsilon) \tag{1}$$

where $P(\cdot)$ represents our belief in H given ϵ. The utility function $U(\cdot)$ encodes the preferences of the decision maker on a numerical scale.

We use the maximum expected utility principle to take the best decision, meaning selecting an option a^* such that

$$a^* = \mathrm{argmax}_{a_i \in A}\, EU(a_i) \tag{2}$$

2.2 Dynamic Influence diagram

Dynamic influence diagrams introduce discrete time to the model. The time-sliced model is constructed based on the static network, with each time slice having a static structure while the development of the system over time is specified by the links between variables of different time slices. The temporal links of a time slice are the set of links from variables of the previous time slice into variables of the current time slice. The interface of a time slice is the set of variables with parents in the previous time slice. A dynamic model can be seen as the same model put one after the other, each model representing the system state at a single time step and the connections from one time step to the next time step represent the influence of the past state of the system on the current state of the system as illustrated in fig. 1. In our experiment, we use a model with a finite horizon dynamic influence diagram.

3 Simulation and Validation

We utilize a formaldehyde production simulator to assess the potential of dynamic influence diagrams as decision support for operators in control rooms.

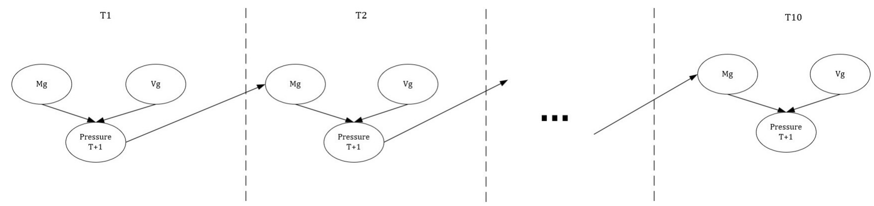


Fig. 1. Structure of a dynamic model with 10 time-slices. We calculate "Pressure T+1" at time T using Mg and Vg. Then "Pressure T+1" is used to calculate the amount of substance Mg at T+1.

3.1 Test Environment / Formaldehyde Production Scenario

Our study employs a simulated interface of a modified formaldehyde production plant, as outlined in [2]. The plant approximates a production rate of 10,000 kg/hr of 30% formaldehyde solution, generated via the partial oxidation of methanol with air. The simulator comprises six sections, namely: Tank, Methanol, Compressor, Heat Recovery, Reactor, and Absorber. With the inclusion of 80 alarms of varying priority levels, the simulator also accounts for nuisance alarms (irrelevant alarms). The simulator's main screen is visible in fig. 2 and the detail tank mimic can be seen in fig. 3. To test the efficiency of our decision support, we created two scenarios:

1. Pressure indicator control failure. In this scenario, the automatic pressure management system in the tank ceases to function. Consequently, the operator must manually modulate the inflow of nitrogen into the tank to preserve the pressure. During this scenario, the cessation of nitrogen flow into the tank results in a pressure drop as the pump continues to channel nitrogen into the plant.
2. Nitrogen valve primary source failure. This scenario is an alternative version of the first one. In this case, the primary source of nitrogen in the tank fails. The operator has to switch to a backup system. While the backup system starts slowly the operator has to regulate the pump power to maintain the pressure inside the tank stable

3.2 Construction of the model

In this section, we provide a detailed explanation of the process involved in constructing the dynamic influence diagram. This diagram can be seen in fig. 4. The primary objective of this model is to detect anomalies and offer the operator an optimal procedure to follow.

Anomalies detection An anomaly is identified when a variable deviates from its intended set point or the default value preordained by the automatic control mode. For the purpose of anomaly detection, we utilize conflict analysis as

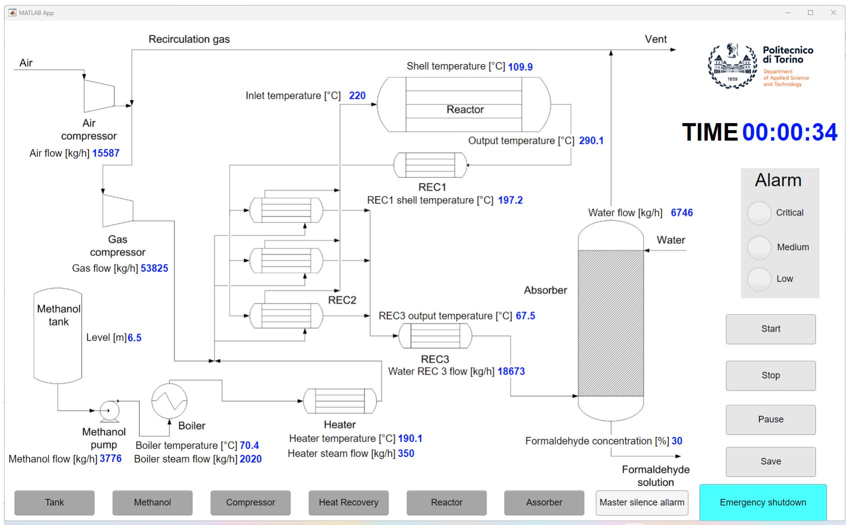


Fig. 2. Process flow diagram of the Production. The formaldehyde is synthesized by combining methanol and compressed air, heating the mixture, initiating a chemical reaction in the Reactor, and finally diluting the solution in the Absorber to obtain the appropriate concentration. At the bottom is the different mimic that the operator can open on another screen for a process flow diagram of a specific part of the plant (see fig. 3)

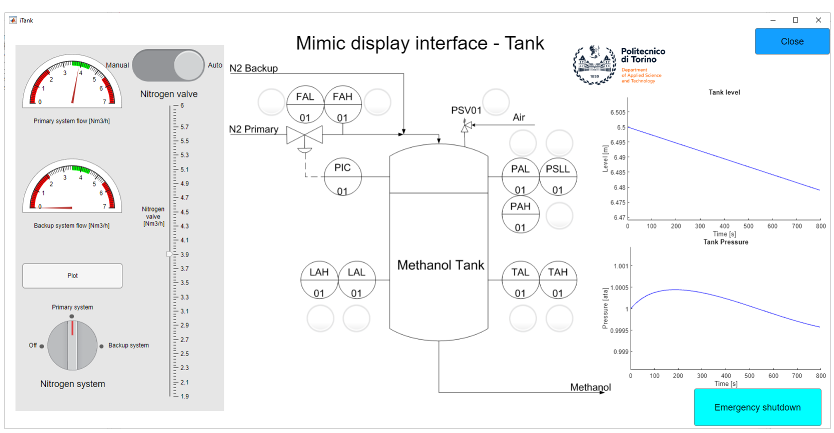


Fig. 3. Overview of the Tank section. On the left, we can see the nitrogen flow control panel. In the middle, the process flow diagram of the tank with all the possible alarms. And on the right the graph of the physical value that need to be monitored by the operator

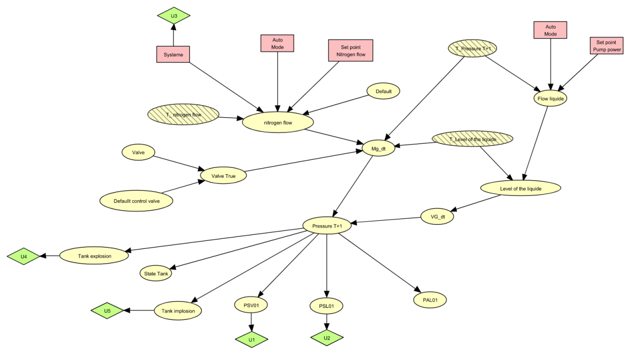


Fig. 4. Model designed for the scenarios. Pink nodes indicate decision variables: "Auto" (on/off states), "Set point" (representing nitrogen flow or pump power set points), and "System" (Primary/Secondary states reflecting the system in use for nitrogen flow). Yellow nodes represent random variables like physical values, faults, and alarms. Striped nodes indicate past variables affecting the current state. Green nodes are cost associated with a specific state of the parent's nodes. We made the assumption that each decision are independent from the states of the system

described in [1] within the influence diagram. Conflict in the influence diagram context is assumed when the evidence disseminated through the model exhibits inconsistencies or contradictions. Specifically, a conflict arises when the product of the individual probabilities of each evidence exceeds the joint probability of all evidence. Consider a set of evidence, $\epsilon = (\epsilon_1, \dots, \epsilon_n)$. We define the measure of conflict as follows:

$$\mathrm{conf}(\epsilon) = \mathrm{conf}([\epsilon_1, \dots, \epsilon_n]) = \log(\prod_i \frac{P(\epsilon_i)}{P(\epsilon)}) \tag{3}$$

A conflict is flagged if $\mathrm{conf}(\epsilon) > 0$. Such conflicts can often be rationalized by a hypothesis, denoted by h, with a low probability of occurrence. If $\mathrm{conf}(\epsilon \cup h) < 0$, it implies that h accounts for the conflict. In our model, h represents a fault within the system. Consequently, if a fault is capable of explaining a conflict, it is detected and identified as such.

Parameter and structure specification The parameter specification relies on these physical equations related to the process as outlined in [2]. Owing to the discretization of the variables, we utilize a sampling technique to formulate the resultant Conditional Probability Table (CPT). To demonstrate this methodology, we consider the calculation of pressure from our case study.

The pressure is contingent on two variables, Mg_dt (mole) and VG_dt (m^3), abiding by the perfect gas law:

$$\mathrm{PV} = \mathrm{nRT} \tag{4}$$

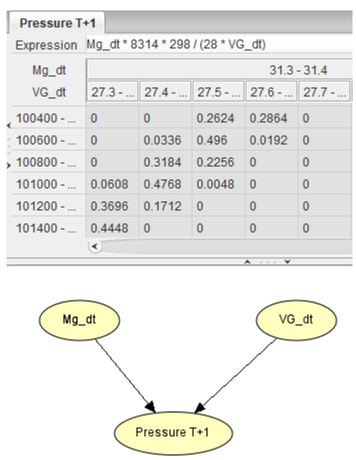
In our experiment, the corresponding physical equation is:

$$\mathrm{P} = \mathrm{Mg\_dt} * 8.314 * 1000 * 298/(28 * \mathrm{VG\_dt}) \tag{5}$$

Where P is expressed in Pascal, MG_dt in Kg, and VG_dt in m^3. The temperature, 298, is in degrees Celsius, 8.314 J/(mol*K) is the perfect gas constant, and 28 is the molecular mass of methanol (kg/kmol), which is divided by 1000 to convert to (kg/mol).

We build the structure of the model according to the formula. The pressure depends on Mg_dt and VG_dt. We link them to the Pressure node. We also use this formula to set the expression in the pressure node. The graph can be seen in fig. 5. Additionally, it is worth mentioning that Mg_dt and VG_dt serve as intermediate variables in order to avoid directly connecting all variables to the pressure node, which would result in a too-large conditional probability table. It has also the benefit to display the model of the different physical equations in a comprehensible way.

The CPT is generated by employing a sampling method. In this study, we sampled 25 values within each interval for each state interval of the parent nodes Mg_dt and VG_dt. Subsequently, we estimate the probability of a point falling within the state intervals of "Pressure T+1" after applying the formula.



Pressure T+1

Expression Mg_dt * 8314 * 298 / (28 * VG_dt)

Mg_dt	31.3 - 31.4				
VG_dt	27.3 - ...	27.4 - ...	27.5 - ...	27.6 - ...	27.7 - ...
100400 - ...	0	0	0.2624	0.2864	0
100600 - ...	0	0.0336	0.496	0.0192	0
100800 - ...	0	0.3184	0.2256	0	0
101000 - ...	0.0608	0.4768	0.0048	0	0
101200 - ...	0.3696	0.1712	0	0	0
101400 - ...	0.4448	0	0	0	0

Fig. 5. Exemple for the calculation of the Pressure

Utility We employ nodes within the model to encapsulate the potential outcomes, which signify the ultimate incidents that may occur in the industrial plant. Post the propagation of the observed values and decisions via the influence diagram, we ascertain the likelihood of these consequences. Each consequence node is coupled with a utility node that encapsulates the financial impact associated with the probable outcomes. For instance, the financial implication of a tank explosion is estimated to be one million dollars. These cost assessments are derived based on references such as [2]. The likelihood of a tank explosion is influenced by other contributing factors, such as pressure or flow rates.

Dynamic model We employ a dynamic influence diagram for real-time process monitoring, aiming to predict critical events and provide operators with advanced warnings. The model operates over a span of 10 time steps, each step representing 1 minute. Hence, the model provides a future projection of the system state at 1-minute intervals over the next 10 minutes. This time frame was chosen to accurately capture the system dynamics.

With this setup, we can alert the operator to any impending critical event within the next 10 minutes and offer them an optimal course of action to either avert or mitigate the event. In our simulation, approximating the dynamic model with a 10-time step model is sufficient for addressing the scenario which lasts for 15 min. It's also worth noting that adding further time steps does not influence the recommendations provided across different scenarios.

3.3 Use of the model

The model is used to detect anomalies and propose the optimal set of actions for the operator. We can separate the use of the model into 3 different steps:

1. First, the current state of the process is assessed by inserting observable data. The decision node "Auto Mode" has by default state "on" and the "System" node has by default state "Primary". During this phase, anomalies are identified by considering all hypotheses that reduce conflicts. Additionally, potential critical events are predicted.
2. Next, we incorporate both the observed data and the anomaly identified in the previous stage. We then evaluate various actions for their maximum utility in each time step, thereby formulating an optimal set of actions intended to either prevent or mitigate a potentially critical event. (Given that the actions are examined sequentially for their utility, they should be logically ordered to ensure they are presented correctly to the operator.)
3. Finally, the operator is presented with the optimal procedure, which outlines the recommended course of action based on the preceding analyses.

Scenario 1. In the first scenario of our study, an issue arises with the nitrogen flow being lower than expected due to a malfunction in the automatic control system. The evidence of node "Auto" being in the state "on" creates a conflict with the nitrogen flow value since, in auto mode, the flow of nitrogen should be higher. By setting the "Fault" node to the state of "control valve failure," the conflict is resolved. At this stage, the model represents the current state of the system, considering the failure. Upon analysis, it is found that switching the "Auto" mode to the state "off" and manually adjusting the set point of the nitrogen flow to a value between 3.5-4.5 m^3/h are the actions with the maximum utility. These two actions are then recommended to the operator with the indication of the failure.

By utilizing this approach, we employ a single model to evaluate the current state of the system, forecast future states, and suggest the optimal procedure for the operator. It is crucial to emphasize that these procedures are continuously updated and can adapt to system changes. This framework provides a solid foundation for developing efficient procedures. Those procedures presented to the operator are shorter compared to the standard procedure as it focuses solely on the necessary action. A classical procedure consists of troubleshooting, action, and monitoring phases. The decision support system assists the operator in decision-making without replacing the initial procedure. Instead, it complements the existing procedure by offering recommendations in difficult situations. This approach offers a comprehensive solution, enhancing operators' decision-making processes and ultimately improving overall system performance.

4 Results and Discussion

A preliminary study was done to assess the performance of the decision support system. The performance was asses in terms of workload and situation awareness.

4.1 Assessment of DID's Effectiveness in Situational Response

The pilot study evaluated the impact DIDs on reducing workload and enhancing situational awareness, initial findings indicate positive outcomes. Two groups of participants were formed: one without decision support and the other with decision support. The first group comprised three participants, while the second group consisted of four. All participants experienced three different scenarios. Following each scenario, the workload and situational awareness were assessed using the raw-NASA-TLX[6] and SART[7] questionnaires. The raw NASA-TLX results are shown in fig. 6, and the SART results are displayed in fig. 7. We calculated the average scores across all scenarios within each group.

The group utilizing decision support demonstrated a lower workload, except in performance and physical demand. One plausible explanation for the observed variations in the physical demand variable could be its lack of relevance to this study, leading participants to interpret it differently. Moreover, the decision support system group exhibited improved situational awareness, particularly in terms of concentration, information gain, and information quality. However, the questionnaire show also an increase in task complexity. Additionally, when asked questions about the understanding of the situation at three different times of the task to assess their situation awareness the score of the participant without decision support was 3.8/5 and 2.8/5 for those with. This result balances the questionnaire result and indicates potentially people following blindly the recommendation without clearly understanding the situation.

Individuals using decision support demonstrated faster response and problem resolution compared to those without it. The limited number of instructions the decision support system provided resulted in nearly immediate response times when followed by the users.

These findings, while based on a small sample size, indicate the potential of DIDs to enhance significantly decision-making for control room operators and improve overall safety in complex industrial processes. To further validate these results, more participants will be included in future studies.

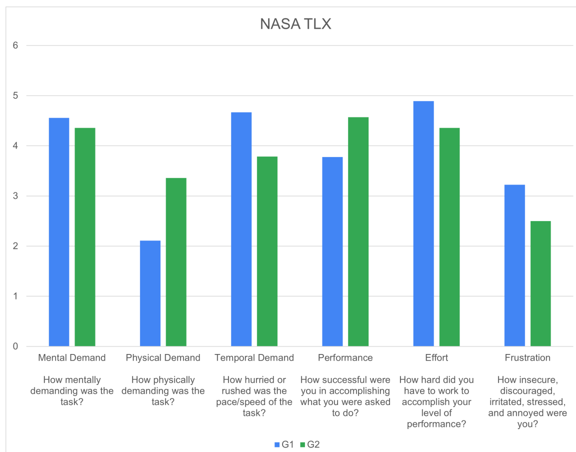


Fig. 6. Raw NASA-TLX for G1 without support and G2 with support.

4.2 Limitations and Future Improvements

A noteworthy constraint of the model lies in effectively conveying the set of recommended actions to the operator. While it is possible to develop an optimal course of action for the ensuing 10 minutes, communicating this information effectively poses a significant challenge. Striking an equilibrium between providing exhaustive details about required actions and the cause of the deviation—which could potentially overwhelm the operator and offering sparse information which may lead to operator distrust in the decision support system is essential.

Moreover, as the current model is relatively compact, identifying the anomaly that explains the conflict is straightforward. However, for a more expansive model with multiple possible anomalies, a more precise algorithm may be required. In this regard, a conflict localization algorithm has been proposed in [9] to concentrate solely on the specific sections of the model where the conflict originates.

The process of discretization plays a pivotal role in the results. If the pressure is discretized with large intervals, the model may overlook the impact of changes in the nitrogen flow variable. Conversely, if the discretization of the pressure

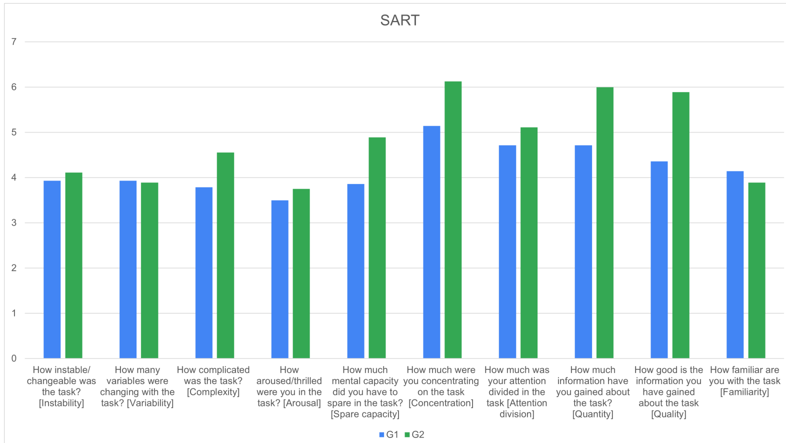


Fig. 7. SART questionnaire for G1 without support and G2 with support.

variable is too granular, it could substantially enlarge the Conditional Probability Table (CPT) of the "MG_dt" variable. This could result in a model with such high computational demands that its live use becomes impractical. Balancing the need for precise outcomes with maintaining manageable sizes for CPT presents a formidable task. Potential developments to address this challenge can be found in [10].

Further consideration of these support systems involves the need for productive cooperation between the operator and the system. The support should be carefully designed to help the operator and not be a nuisance. The concept of human-automation decision-making is explored in detail in [11].

One potential enhancement to the model could be to consider the operator's physical and mental state to tailor the decision support accordingly. In this approach, the model would account not only for system data but also operator-specific data, thereby providing personalized and optimal decision support. Noteworthy research has already been conducted in this area, as referenced in [12].

5 Conclusion

In this paper, we propose the use of dynamic influence diagrams (DIDs) as a decision support system to enhance control room operator decision-making in the context of formaldehyde manufacturing. The study highlights the challenges faced by control room operators, such as task overload and cognitive biases, and presents DIDs as a solution to address these issues. By monitoring the process over time and detecting anomalies, DIDs can provide operators with support for the most effective course of action. The effectiveness of the approach is tested using a simulated formaldehyde production environment, and the results demonstrate some evidence of reduced workload but also potentially reduced situation awareness when using the support system. The result needs to be put in the perspective of the few number of participants and this research is continuing to produce more statistically significant results. The research represents an important step towards developing intelligent decision support systems for the process industries. However, effectively conveying the instructions to the operator can be challenging. Future research will be focused on adapting the support to the state of the operator. Overall, the use of DIDs shows promise in enhancing control room operator decision-making and improving situational awareness in industrial settings.

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