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Original Article

A water treatment case study for quantifying model performance with multilevel flow modeling

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ABSTRACT

Decision support systems are a key focus of research on developing control rooms to aid operators in making reliable decisions and reducing incidents caused by human errors. For this purpose, models of complex systems can be developed to diagnose causes or consequences for specific alarms. Models applied in safety systems of complex and safety-critical systems require rigorous and reliable model building and testing. Multilevel flow modeling is a qualitative and discrete method for diagnosing faults and has previously only been validated by subjective and qualitative means. To ensure reliability during operation, this work aims to synthesize a procedure to measure model performance according to diagnostic requirements. A simple procedure is proposed for validating and evaluating the concept of multilevel flow modeling. For this purpose, expert statements, dynamic process simulations, and pilot plant experiments are used for validation of simple multilevel flow modeling models of a hydrocyclone unit for oil removal from produced water.

1. Introduction

Decision support systems are crucial in attempts to improve the efficiency and safety of control systems. With an increase in system complexity and autonomy, tasks for operators to analyze situations to determine behaviors that deviate from nominal system operation are becoming increasingly complicated. Automated fault diagnosis is a method that can potentially decrease the reaction time and increase the probability of correct responses to faults. The focus of online fault diagnosis has primarily been at the component level. Multilevel flow modeling (MFM) is a method for modeling the functionality of complex mass and energy flow systems. The method is used to model how low-level functionality supports high-level functionality, commonly referred to as means-end modeling. Models of nuclear power systems, electric power grids, and oil production systems have been used for online fault diagnosis [1].

MFM has numerous different applications, of which online fault diagnosis is one. Online fault diagnosis with MFM is, however, limited in application [1–6], whereas offline root cause analysis has been applied diversely. Current methods for model validation of MFM models are limited in application, as the models primarily have been used for offline root cause analysis. The models must be reliable if they are to be used for online fault diagnosis in industrial decision support systems. Insufficient validation of models to improve decision reliability may prove to be counterproductive when seeking to improve the level of safety.

No additional requirements are defined for advanced or intelligent control algorithms or for diagnostic methods in standards as NORSOK I-002 on Safety and Automation Systems [7]. In cases of false or absent alarms and diagnoses, operators may eventually ignore decision support systems and solely rely on their own experience and intuition. In line with the concept of defense in depth [8], fault diagnosis is used as an addition to the monitoring level, at level 2, to enable either prevention or mitigation of faults. To the same degree as an emergency shutdown, a fault diagnostic system should thus be considered a safety precaution, although its function according to the defense in depth concept is at a different level. Model validation and testing is thus crucial.

This article introduces initial work on an approach to validate MFM models based on different types of available information. It has been applied to simple MFM models of a deoiling hydrocyclone. The aim is to provide a measure of model performance.

2. Previous validation

MFM is a strictly qualitative method. Numerical process signals are used but only to produce qualitative and discrete states such as low, normal, or high. The states are then processed by the MFM reasoning in combination with the MFM model. The discrete states simplify the rule base and thus the reasoning process, significantly, and ensure low computational effort when dealing with plant-wide fault diagnosis [1]. Systems have typically been modeled and validated by an expert in MFM and a process expert. Based on the model, functions are triggered separately, and the prognosis is compared to the causes and consequences as explained by a process expert. Alternatively, an MFM and/or a process expert attempts to describe how the MFM prognosis relates to the dynamics of the process system. This approach is subjective and qualitative. In addition, it introduces bias to the validation, as there is no distinction between the input used to build the model and that used to validate it.

The majority of published research on the topic of MFM is not concerned with the validity of the models. This is very problematic, as many models are presented with no information on how well they model the physical system. The published research addressing validation includes examples of comparisons of expert statements to cause consequence fault trees, to counter actions generated based on MFM model prognoses, and to fault trees published in scientific literature [9–11]. More recently, model prognoses have been compared to standardized operation procedures available in published standards, and to numerical process simulations [12]. The standardized operation procedure and MFM prognoses were presented in a table for easy comparison as a basis for a qualitative evaluation [13]. In addition, different theoretical aspects of MFM model validation are discussed in the study by Wu et al. [14]. All the previously mentioned approaches focus on the validity of the model according to the output produced by a specific input. Causal relations between functions have been discussed by Larsson et al. and Berquist et al., and a correlation method was presented to determine the causal relationship between functions [15,16]. The validity of the causal relationship is the only example of validation of the structure of MFM models. Apart from this, the structure is only treated as a part of the verification, according to a defined MFM syntax [14].

3. Hydrocyclone

The validation method is demonstrated using a simple case study of hydrocyclone equipment for water treatment. A hydrocyclone is a passive component used for separation of water and oil in offshore Produced water treatment (PWT). It has one inlet and two outlets. If the process conditions are optimal, the oil dispersed in the water leaves the hydrocyclone through the overflow outlet and the treated water leaves through the underflow outlet, as shown in Fig. 1.

The common control strategy is based on the pressure drop ratio (*PDR*), defined as the ratio of the pressure difference from inlet to overflow ΔP_o to that from inlet to underflow ΔP_u as shown in Eq. 1 [18].

$$PDR = \frac{\Delta P_o}{\Delta P_u} = \frac{P_i - P_o}{P_i - P_u} \tag{1}$$

As the density of water is higher than that of oil, the centrifugal force of the water exceeds the centrifugal force of the oil particles. The inlet flow enters tangentially into the conical geometry of the hydrocyclone, thus passively generating a rotational flow. This results in the water moving outwards, toward the hydrocyclone wall, in a vortex; the oil is displaced toward the center of the hydrocyclone, in a vortex.

The separation efficiency of the hydrocyclone does not only depend on the *PDR* but also on the flow split F_s, inlet flow rate, oil content, oil droplet size, and geometry. The flow split is proportional to the *PDR*, and it can be defined as the ratio between the overflow flow rate Q_o and the input flow rate Q_i [17]:

$$F_s = \frac{Q_o}{Q_i} \tag{2}$$

The *PDR* is controlled using two control valves, one at each outlet. A P&ID of the hydrocyclone used for experimental work is shown in Fig. 2. The setup has a pressure and a flow rate sensor on all inlets and outlets and one control valve on each outlet. The input water is delivered from a water tank by a pump. Both the underflow and overflow outputs are transported to the same water tank.

The standard offshore application of hydrocyclones involves upstream separation, in combination with three-phase separation tanks. The underflow valve is then used to control the water level in the three-phase separation tank, and the overflow valve controls the PDR. In this application, any other processes besides the hydrocyclone are bypassed, and the underflow valve has no real-time control. In a standard application, the hydrocyclone is placed in a bundle of hydrocyclones, among which the inlet water is divided. This is however not the case in this particular application, in which only a single hydrocyclone is used.

4. MFM model

As a case study, only a part of the full MFM model of the hydrocyclone will be used to prove and present the principle of this validation method. This part is the mass flow, shown in Fig. 3. As can be seen in the figure, there are six transport functions, of which three represent the three flow rate sensors and three storage functions representing the pressure sensors. A balance function represents the mass balance of flow from the inlet to the underflow and the overflow.

The model shown in Fig. 3 can potentially be used in two different models, by having two different representations of the sensors. The mapping from component to function will thus be the only difference between the two models: v1 and v2. The MFM models and their respective mappings are shown in Table 1. The third model, v3, is similar to v2, but the causal relation in2 has been
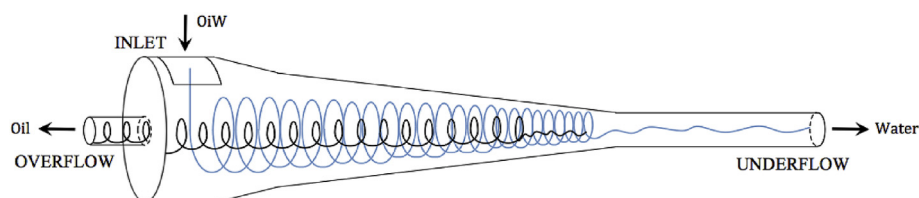

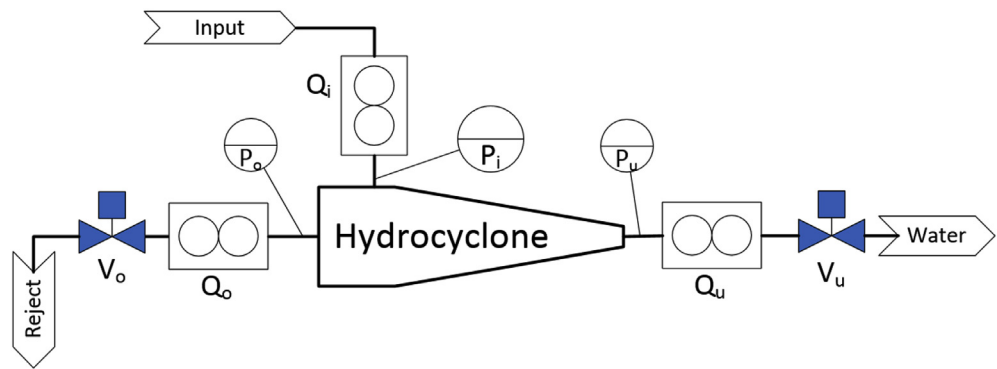**Fig. 1.** Example of water and oil flow in a hydrocylone [17].
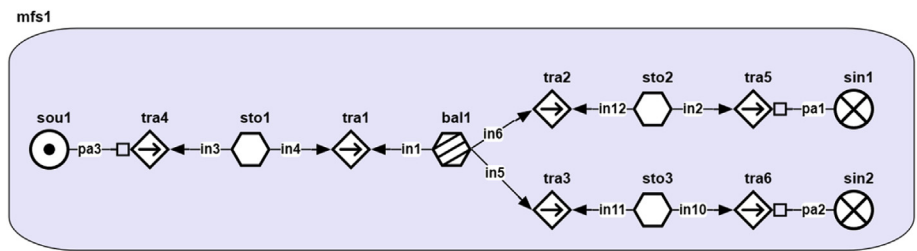
Fig. 2. P&ID of the hydrocyclone at the pilot plant.

Fig. 3. MFM Model of hydrocyclone mass flow separation.
MFM, multilevel flow modeling.

Table 1
MFM models for Fig. 3.

Model	Q_i	Q_u	Q_o	P_i	P_u	P_o	Relation
MFM v1	tra1	tra3	tra2	sto1	sto3	sto2	
MFM v2	tra4	tra6	tra5	sto1	sto3	sto2	
MFM v3	tra4	tra6	tra5	sto1	sto3	sto2	in2 $\rightarrow$ pa4

MFM, multilevel flow modeling.

changed to pa4. It is thus a participant relation, instead of an influencer relation. Influencer relations can propagate state changes in any direction, whereas a participant relation can only propagate in one direction [19].

5. Validation method

The purposes of having a structured methodology for validating MFM models for fault diagnostic applications include:

1. Performance comparison of one model, on different sets of faults, to determine the suitability of MFM models for specific faults or systems.
2. Comparison of different models and model versions on the same set of faults to track and ensure progression during model building.
3. Comparison of different extensions of the MFM methodology on the same set of faults to track and ensure improvement in development of the MFM methodology, e.g., the rule base and reasoning.
4. Performance comparison of MFM with other fault diagnostic methods on the same set of faults to determine the suitability of MFM for specific systems or faults, compared to other methods.

A graphical illustration of these four purposes is shown in Fig. 4. The figure depicts the defined sets of faults, marked by bold circles, in comparison to diagnostic prognoses or predictions, marked by

filled circles. If a model can predict all of the defined faults, the bold and filled circles align and are equal in size. Two different methods, models or MFM extensions may have very similar performance on a set of faults, but given that the criteria under which they are evaluated change, the performance may no longer be similar. In this work, only a single criterion is proposed; however, this may very well prove to be insufficient for model validation in many cases.

Validation of MFM models can be separated into three stages based on the information available at each stage. These stages are *System Concept*, *System Design* and *System Operation*.

In the first stage, *System Concept*, the only available information may very well be P&ID diagrams, expert statements, and preliminary Hazard and Operability Study (HAZOP) results. This information can be used to build the MFM model and validate it. In the next stage, *System Design*, flowsheets, mass, energy, and momentum balance calculations, and process module specifications and dynamic process simulations (DPSs) may be available. The final stage, *System Operation*, could very well be carried out as a part of commissioning. At this stage, the physical system is available for experimentation and can thus include online diagnosis of faults emulated on the physical plant. For this work, a pilot plant (PP) of an offshore PWT system will be used. The validation procedures for each stage are shown in Fig. 5. This figure shows how experts first define the faults, which are then compared to the MFM prognoses. In addition, the defined faults are simulated or emulated, and the results are then compared to the MFM prognoses. For new plants, the amount of information available that will most likely be largest is the type of information associated with the System Concept stage; the lowest amount of information will be that associated with the System Operation stage.

The previously published validation approaches are all related to the System Concept stage, apart from the methods introduced by Larsson et al. and Wu et al. [15,16,12–14]. The validation of MFM models at each stage can be considered as engineering validation of the models. Future extensions of the work presented here will
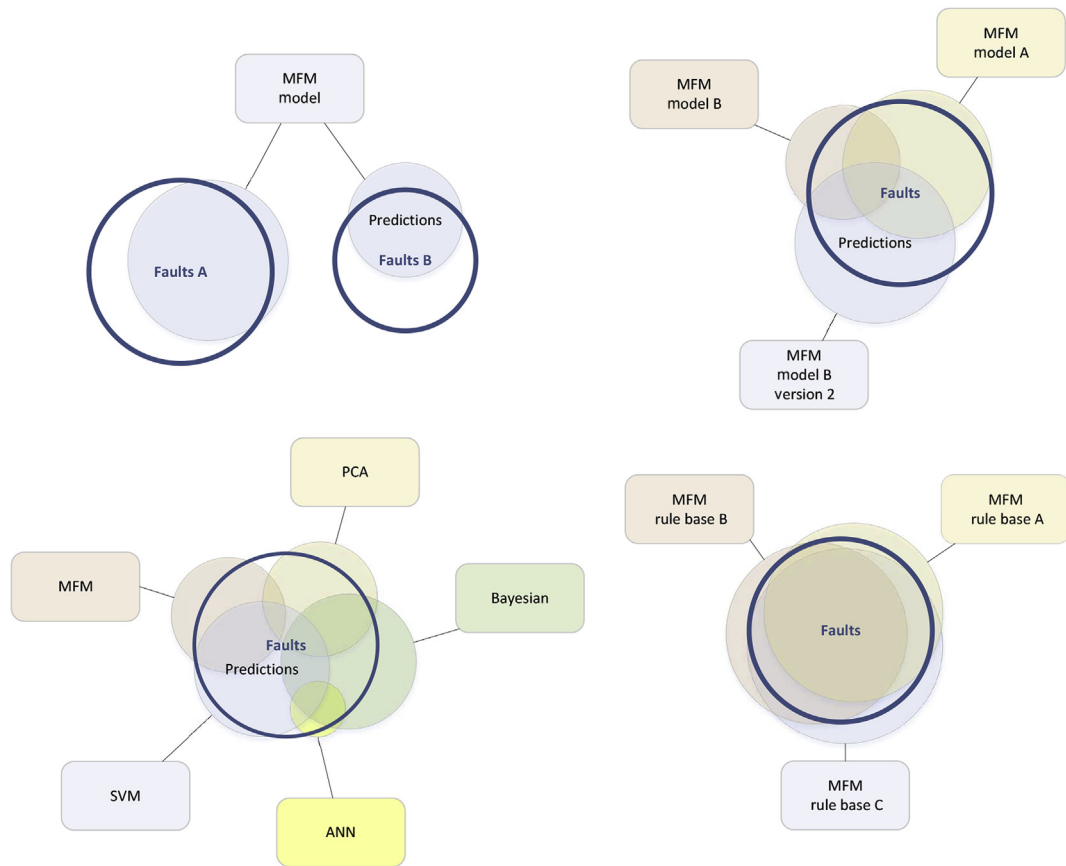
Fig. 4. Model comparison of MFM on fault sets by performance evaluation.
MFM, multilevel flow modeling; PCA, principle component analysis; SVM, support vector machine; ANN, artificial neural network.
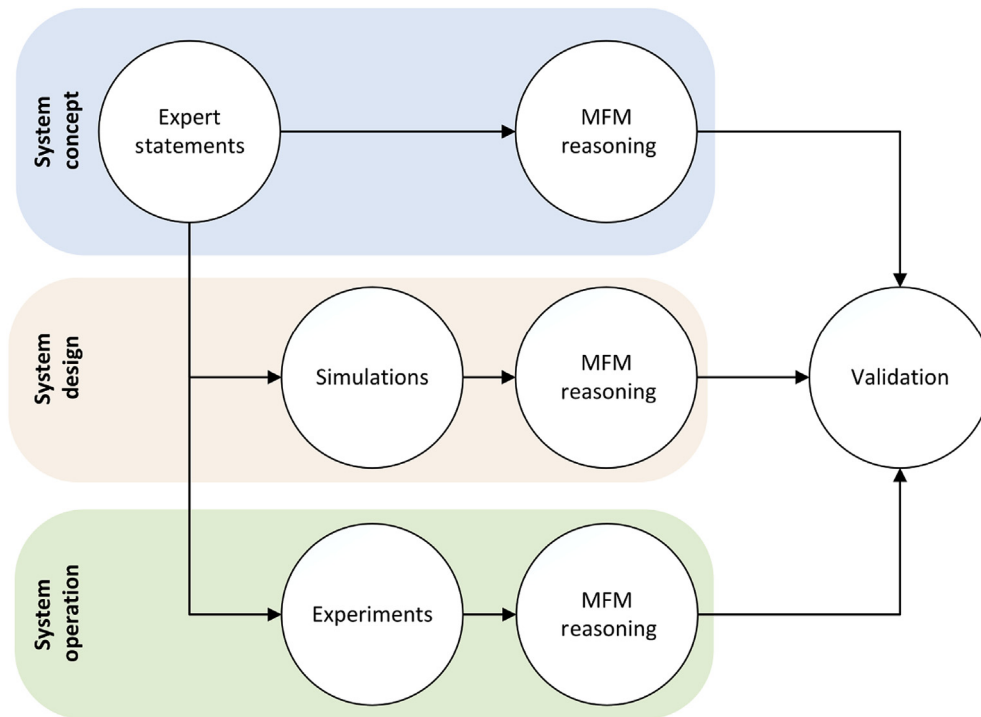

Fig. 5. Modeling and validation stages of MFM models.
MFM, multilevel flow modeling.

include a scientific validation of the three approaches to engineering validation. The scientific validation will combine validation sets and information of different types, from each of the three stages, and will examine the discrepancies between the validation sets. In the case of no or only little discrepancy, it is assumed that models can be validated at each stage by using this procedure.

6. Validation

Conventional diagnostic methods are used to model a defined set of faults and to distinguish between these faults and any other behavior. In theory, MFM can distinguish between faults that have not been defined. MFM models describe the system's functionality at a generic and qualitative level and are thus capable of generating propagation paths and prognoses automatically, based on evidence.

For this reason, it is important to also validate the structure of the model and not only the prognoses. To increase the fidelity of such prognoses, it is important that the model representation of the system behavior, functionality, and causality is correct. This article deals with the validity of the causal relations between functions to determine how well they reflect the physical system. The functions are then assumed to be modeled correctly. If such relations are valid, the nonvalidated prognoses of the MFM model will be assumed to be correct.

For the case study of the hydrocyclone, four scenarios have been defined and tested for each of the three stages. Valve openings of the underflow valve V_u and the overflow valve V_o have individually been increased and decreased by a defined amount. The scenarios were implemented as a position control offset of the valve setpoint in both the DPS and the PP. An overview of how the scenarios have been implemented in MFM, in the PP, in the DPS, and as expert statements is shown in Table 2. The valve position range for V_u and V_o is between [0 100%], where 0 is fully closed and 100% is fully opened.

6.1. System concept

At the concept level, no numerical information will be available apart from what can be found in the literature. The only other source of information at this stage will most likely be estimations and experience-based statements of experts. When designing chemical process systems, a HAZOP will be carried out for compliance with safety regulations. The format of a HAZOP is as follows:

1. Which hazards can arise, given physical property (flow rate) changes (increases) in the hydrocyclone?
2. What are the causes?
3. What are the consequences?
4. What are the safeguards?

Thus, the purpose is not to identify the system behavior but to identify safety-critical operation and the corresponding causes and consequences. In addition, safeguards must be proposed to mitigate faults. However, as this method is based on a physical property,

such as the flow rate, and an instance, such as a decrease, it can be used as a basis for specifying the operational behavior in a structured manner when identifying causes and consequences of the given properties. A HAZOP is based solely on expert statements. For this work, expert statements have been acquired from operators of the PP and compiled into a qualitative trend table (QTT) in Table 3. HAZOP has however not been used for the work presented here. In all the QTTs, the + represents an increasing qualitative trend of a property, and − a decreasing qualitative trend. Each column represents a physical property, and the rows represent scenarios.

6.2. System design

DPSs of the hydrocyclone have been carried out in K-spice. K-Spice is a software for simulating process conditions of offshore oil production plants, with the intent of plant design.

The model, shown in Fig. 6, includes a hydrocyclone module, an overflow and an underflow control valve, and a PID controller for the overflow valve. The underflow valve has been given a specified setpoint with no control. This model has not been calibrated, and thus produces results different from those of the PP. It is assumed that this difference is only numerical, but no differences exist at the qualitative or causal levels between the PP and the model behavior.

Based on the experiments for the DPS listed in Table 2, a QTT has been compiled in Table 4. It is assumed that the magnitude of an increase or decrease is of no importance for assessing the validity of how a high or low alarm state is propagated through a model. The scenario for a closing overflow valve is shown in Fig. 7 with the overflow valve position and the inlet, underflow, and overflow pressures. As the valve closes, the pressure increases at the inlet, underflow, and overflow. This indicates a causal relationship between the valve and the pressure at the inlet, underflow, and overflow. It does not however necessarily indicate direct causal relations. In MFM models, the order in which something can be causally propagated is directly defined; however, for the results from the DPS, the causal order is not directly given.

6.3. System operation

The scenario for the opening of the underflow valve in the PP is shown in Fig. 8. The function *findchangepts* from MATLAB [20] has been used to determine whether a signal increases or decreases. The function divides a signal into sections based on changes to the signal mean. The signal is divided into sections by varying the section and minimizing the total residual error of the signal from the mean of the sections. The change in mean, from the section before manipulating either V_u or V_o to the section after manipulating it, is used to determine whether the qualitative trend is positive or negative. A value of ±0.5 % has been chosen for thresholding the signal. If the signal mean does not change by more than the defined threshold, the signal is considered as being in a normal state. If it increases by more than 0.5%, it is considered as a high state (+); if it decreases, it is considered as a low state (−). This approach has been used to produce Tables 4 and 5. The PDR and flow split shown in Table 5 have been calculated according to Eqs. 1 and 2.

Table 2
Methods for testing or simulating faults scenarios.

Scenario	Expert	DPS	PP	MFM
V_u +	V_u opens	V_u SP + 3%	V_u SP + 3%	Q_u High
V_u −	V_u closes	V_u SP − 3%	V_u SP − 3%	Q_u Low
V_o +	V_o opens	V_o SP + 20%	V_o SP + 20%	Q_o High
V_o −	V_o closes	V_o SP − 20%	V_o SP − 20%	Q_o Low

DPS, dynamic process simulation; PP, pilot plant; MFM, multilevel flow modeling; SP, valve setpoint.

Table 3
QTT for expert statements.

Scenario	Q_i	Q_u	Q_o	P_i	P_u	P_o	PDR	F_s
V_u +	+	+	−	0	−	−		
V_u −	−	−	+	0	+	+		
V_o +	+	−	+	0	−	−		
V_o −	−	+	−	0	+	+		

PDR, pressure drop ratio; QTT, qualitative trend table.
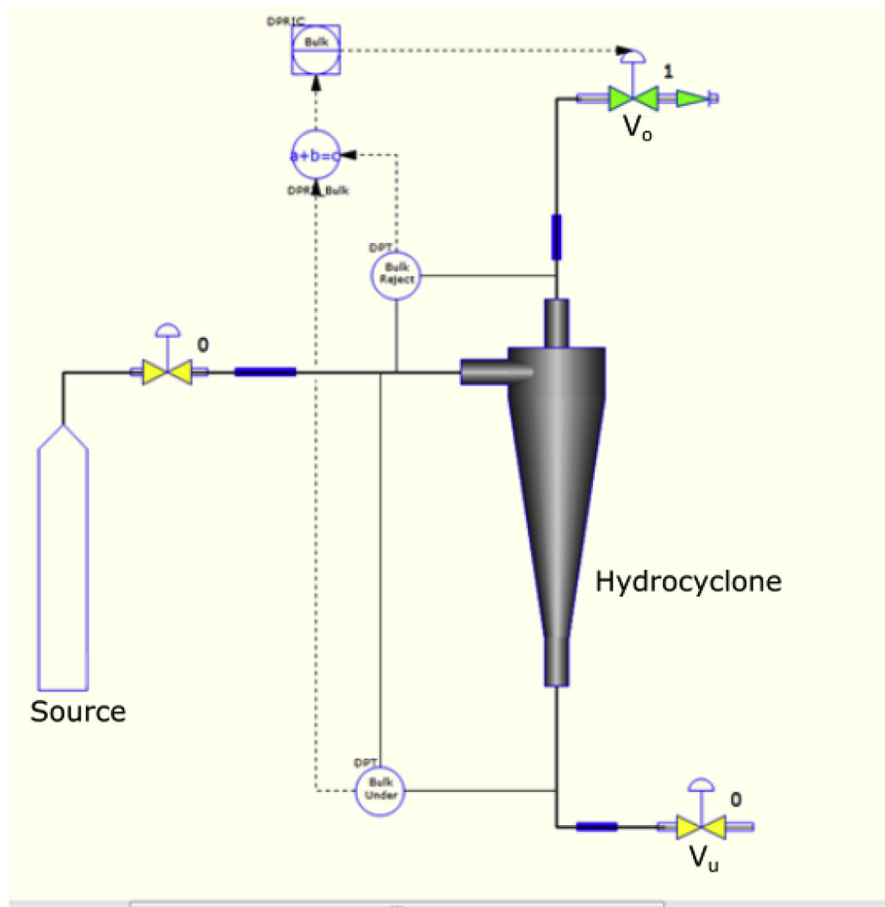
Fig. 6. Model of the hydrocyclone in K-Spice.

Table 4
QTT for the dynamic process simulation (DPS).

Scenario	Q_i	Q_u	Q_o	P_i	P_u	P_o	PDR	F_s
V_u +	+	+	+	−	−	−	0	−
V_u −	−	−	−	+	+	+	−	+
V_o +	+	+	+	−	−	−	+	+
V_o −	−	−	−	+	+	+	−	−

PDR, pressure drop ratio; QTT, qualitative trend table.

6.4. MFM model results

The three MFM models have been used to produce QTTs. For each model, the flow rates Q_o and Q_u are assumed to be directly proportional to the valve openings of V_o and V_u. Thus Q_u has been triggered as high, when reasoning about the consequence of opening V_u. The same applies for Q_o and V_o. The resulting QTT for MFM models v1, v2, and v3 are shown in Tables 6–8.

7. Evaluation

To provide an easily interpretable measure of the model performance, the model output must be compared to validation sets and then quantified. For each scenario, each sensor prognosis from the MFM model has been compared to the result for the same sensor and scenario from a validation set. All three models have been compared individually with all three validation sets.

A confusion matrix has been produced similar to the one shown in Table 9. The validation sets are considered as actual observations and the MFM model outputs as predictions. The matrix has three prediction classes: positive (+), zero (0), and negative (−), corresponding to the states high (+), normal (0), and low (−). When both the validation set and the model predict positive (+), the prediction is classified as a True Positive. The other prediction classes are True Zero, True Negative, False Positive, False Zero, and False Negative. The prediction classes of the false predictions are all followed by either Positive or Negative or Zero, indicating the correct class of the false prediction. Conventionally, confusion matrices are used for evaluation of binary classifiers; however, in this case three classes are used.

The results from only using two classes can be found in the study by Nielsen et al. [21]. As argued in study by Baldi et al. [22], metrics for evaluation of binary classifiers can be extended to multiclass classifiers. Thus, to reflect the possibility of a fault, actuation or system deviation performed so as not to have any consequence on certain functions of the system, the normal state (zero class) has been included.

The confusion matrix for each model, with corresponding validation set, has been used to calculate the accuracy of the MFM model as:

$$Accuracy = \frac{TP + TN + TZ}{TP + TN + TZ + FP + FN + FZ} \tag{3}$$

The accuracy levels of the three MFM model versions compared to those of the validation sets are shown in Table 10. For a model and a validation set, all the individual predictions for each scenario and sensor are summed for each prediction class and used in Eq. 3.
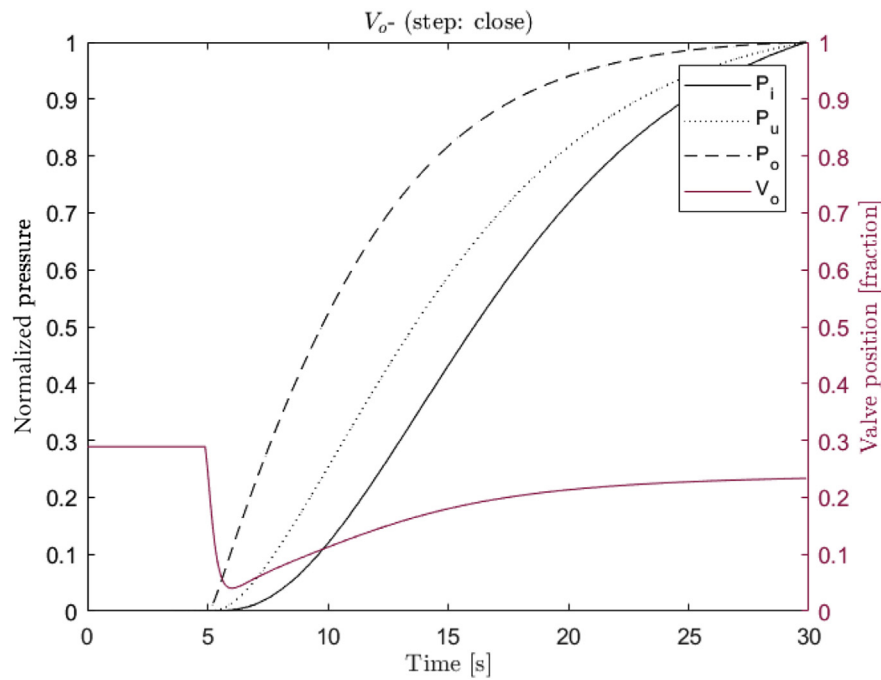
Fig. 7. Response to closing overflow valve V_o in DPS.
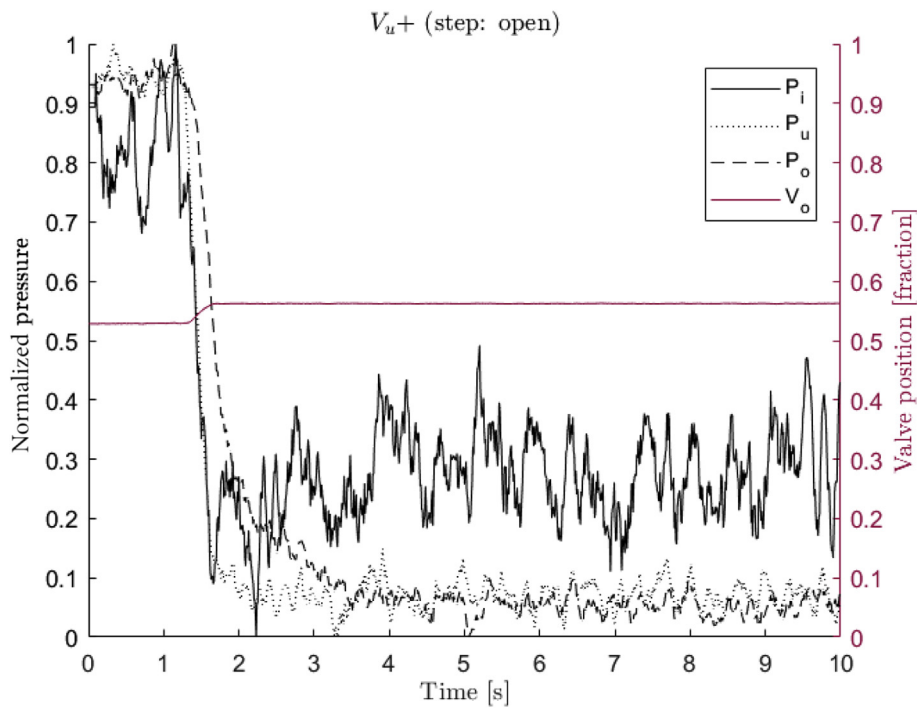DPS, dynamic process simulation.

Fig. 8. Response to opening underflow valve V_u on the pilot plant.

Table 5
QTT for the pilot plant experiments.

Scenario	Q_i	Q_u	Q_o	P_i	P_u	P_o	PDR	F_s
$V_u +$	+	+	−	−	−	−	−	−
$V_u −$	−	−	−	+	+	+	+	+
$V_o +$	0	0	+	0	0	−	+	+
$V_o −$	0	0	−	0	0	+	−	−

PDR, pressure drop ratio; QTT, qualitative trend table.

The mean accuracy of the validation set for all three models is also shown in Table 10, as well as the mean of the accuracy of the model for all validation sets.

It is evident from Table 10 that MFM model v2 is a better representation than model v1, independent of the validation set. Model v3 was made with the intention of achieving a high accuracy on the PP validation set. It achieves the highest accuracy on exactly the PP validation set but has a lower accuracy on the other two sets

Table 6
QTT for the MFM model v1.

Scenario	Q_i	Q_u	Q_o	P_i	P_u	P_o	PDR	F_s
$V_u +$	+	+	−	−	+	−		
$V_u -$	−	−	+	+	−	+		
$V_o +$	+	−	+	−	−	+		
$V_o -$	−	+	−	+	+	−		

PDR, pressure drop ratio; MFM, multilevel flow modeling; QTT, qualitative trend table.

Table 7
QTT for the MFM model v2.

Scenario	Q_i	Q_u	Q_o	P_i	P_u	P_o	PDR	F_s
$V_u +$	+	+	−	−	−	−		
$V_u -$	−	−	+	+	+	+		
$V_o +$	+	−	+	−	−	−		
$V_o -$	−	+	−	+	+	+		

PDR, pressure drop ratio; MFM, multilevel flow modeling; QTT, qualitative trend table.

Table 8
QTT for the MFM model v3.

Scenario	Q_i	Q_u	Q_o	P_i	P_u	P_o	PDR	F_s
$V_u +$	+	+	−	−	−	−		
$V_u -$	−	−	+	+	+	+		
$V_o +$	0	0	+	0	0	−		
$V_o -$	0	0	−	0	0	+		

PDR, pressure drop ratio; MFM, multilevel flow modeling; QTT, qualitative trend table.

Table 9
Multiclass confusion matrix.

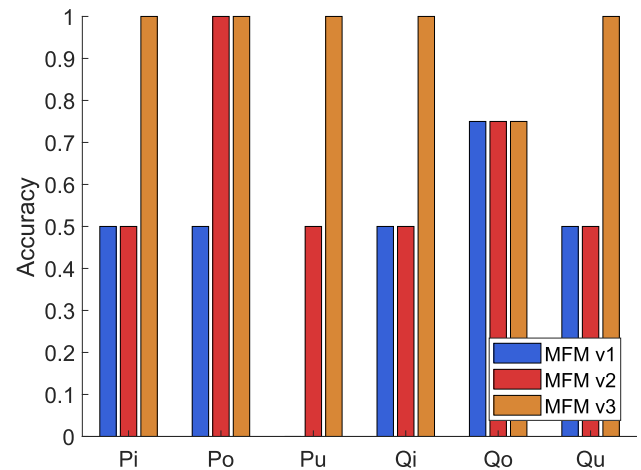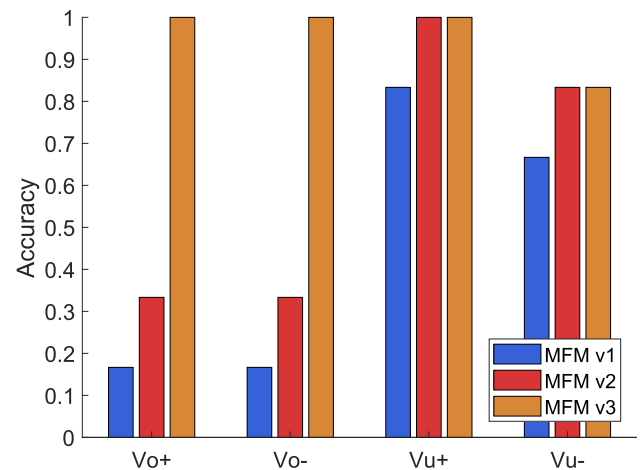|		Predicted MFM		
		+	0	−
Actual validation set	+	TP	FZ(P)	FN(P)
	0	FP(Z)	TZ	FN(Z)
	−	FP(N)	FZ(N)	TN

FN, False Negative; FP, False Positive; FZ, False Zero; MFM, multilevel flow modeling; N, Negative; P, Positive; TN, True Negative; TP, True Positive; Z, Zero.

Table 10
MFM model evaluation.

Model	PP	DPS	Expert	Mean
MFM v1	0.46	0.67	0.67	0.60
MFM v2	0.63	0.83	0.83	0.76
MFM v3	0.96	0.58	0.67	0.74

DPS, dynamic process simulation; PP, pilot plant; MFM, multilevel flow modeling.

Fig. 9. Accuracy of model predictions for each sensor. MFM, multilevel flow modeling.

Fig. 10. Accuracy of model predictions for each scenario. MFM, multilevel flow modeling.

than the accuracy of model v2. An indication of how to improve model v2 can be identified by looking at Figs. 9 and 10. Model v2 has a low accuracy for the two scenarios V_{o+} and V_{o-} but a high accuracy for the two scenarios V_{u+} and V_{u-}. For the sensor predictions from model v2, the accuracy is highest for Q_o and P_o, and the accuracy is 0.5 for all other sensor predictions. This indicates that, when changing V_o in model v2, only the adjacent functions Q_o and P_o are identical to the PP validation set. Q_o must be identical, as the same function represents both Q_o and V_o. The change from V_o is therefore not propagated correctly to the underflow and overflow functions. The specific functions not matching the validation set from the PP can also be found by comparing Tables 5 and 7. From this comparison, it can be seen that the overflow should not affect the underflow or inflow.

The sensors from the inlet and underflow of scenarios V_o in Table 5 have a normal state, as opposed to those in Table 7, which have either a high or low state. Thus, changing the causal relation in2 from an influencer to a participant relation pa4 will decouple the influence of the overflow from the underflow and inlet. This change of causal relation is the change from model v2 to v3. The changes from model v2 to v3 improve the model but only when comparing to the validation set of physical experiments from the PP. The performance is, however, reduced in comparison to the other validation sets.

The QTTs make it easy to improve models by comparing models and validation sets and also allow a quantification of the performance of models. This approach allows us to measure model progression and improvement and can potentially also be used as a quantitative approach to determine if changes to the MFM methodology improve the ability to represent process systems. A similar approach to that in the work presented here will be investigated and applied for the purpose of validating MFM model predictions. The purpose will be to suggest an approach for model validation by measuring how well MFM models can predict root causes or consequences in a data set.

8. Discussion

8.1. Validation sets

Data collected from the actual plant being modeled should be regarded as the validation set with the highest fidelity. As MFM is a discrete method, with no accurate measures, it is important to ensure that nonlinear system behavior does not affect the model performance, or at least to know the degree to which it affects the performance. With only a few samples in the validation set, highly nonlinear behavior can introduce uncertainty to the validation of the model.

Unlike the other validation sets, the results from the PP show that there is no influence from the valve V_o on the inlet and underflow. The orifice of the overflow is very small compared to that of the underflow, thus giving it a very low influence on the system. This result, however, also depends highly on the threshold of 0.5%, under which any deviation is disregarded. The experts are also able to explain this very low influence, but cannot produce statements based on a threshold of 0.5%. The change from an influencer to a participant relation thus reflects this dominance of the underflow over the overflow.

The DPS produced results quite similar to those from the PP. However, the inlet and underflow parameters change for the simulation with changes of the position of V_o, unlike the results from the PP. As this simulation is not exact, the results rely on how the threshold is set. On one hand, a simulation introduces uncertainty when substituted for a physical system, as there are discrepancies between the simulation behavior and the physical system behavior. On the other hand, process variations and sensor noise can be completely avoided, thus eliminating uncertainties introduced by the method used to determine whether a specific scenario results in an increase or decrease of physical parameters.

Results can easily be obtained from experts; however, a lot of uncertainty can be introduced, and this uncertainty can be difficult to identify or quantify. Depending on how expert statements are acquired, the results can possibly vary from time to time or expert to expert.

The input pressure remains constant for all scenarios of the expert statements. The more the structures are provided as constraints, the easier it becomes for the experts to answer. In the PP, a separator is placed upstream from the hydrocyclone. The separator is pressure controlled, and thus the inlet pressure to the hydrocyclone is constant. For this reason, the results are similar to those of conventional plant operation. Had the threshold been increased from 0.5% to 1%, the inlet pressure would have been a zero or normal state for P_i in the V_u scenario for the PP and also a zero or normal state for the simulation for P_i in the V_o state. The PDR and flow split can be influenced by both V_o and V_u. In addition, these variables are functions of two or more physical parameters. This makes the situation more difficult for experts to interpret and reason about; thus, these columns are blank in Table 3.

8.2. Uncertainty

The purpose of model validation is commonly to determine how accurately a model represents something physical. Whether the model does this well or poorly depends on a set of requirements. If these requirements, or the process of validation, does not relate to the actual use of the model, the model performance could possibly be very good. However, when examined during application, the model can possibly perform poorly. As an example of MFM models used for fault diagnosis, a set of tests can be carried out on a physical plant to determine the system behavior. Given that these tests are restricted to a certain process window, the model is validated on data from exactly this process window. The model may, however, be assumed to represent a process window outside of these tests. This introduces uncertainty to the validation process. The uncertainty is thus introduced by any potential model discrepancy that is unaccounted for in the validation process.

As previously mentioned, the method for thresholding signals as either high, normal, or low introduces uncertainty. When validating models, the uncertainties should either be reduced or at least be made explicit, so that whoever is part of the validation process or relies on it is aware of any model limitations. The following issues should in future be addressed, as they introduce uncertainties to the proposed validation method:

- The detection method for a qualitative trend as either high or normal or low.
  - Any parameters or thresholds specific to the detection method.
  - Any assumptions on the nonlinearity of the process and signals
- The choice of test method
- The choice of validation set

As the purpose of validation is to produce accurate and reliable models, for validation of MFM models, the effects of these points should be investigated for the proposed method.

9. Conclusion

To measure model performance, an approach has been presented for validating the causal structure of MFM models. This should enable tracking of model progression, tracking of MFM methodology development, and building of experience on model suitability for specific systems or faults. The approach identifies three stages at which MFM models can be validated with three different types of information: concept, design, and operation stages of process systems. The approach has been applied on three simple MFM models of a deoiling hydrocyclone for offshore PWT. Expert statements, a DPS in K-Spice, and empirical data collected from a PP have been used as validation sets for model validation. For evaluation of binary classifiers, the metric of accuracy has been used to evaluate the MFM model coherence with each validation set. Based on this approach, it was possible to determine a better association of sensors with functions and a better causal representation; this improved the model's coherence with the validation set of the PP. The MFM model achieved an accuracy of 0.96 on the validation set of the PP. This validation approach should provide a structured approach to building and improving MFM models with high fidelity for use in online fault diagnosis and decision support.

Conflicts of interest

There is no conflict of interest.

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