Enhanced reasoning with multilevel flow modeling based on time-to-detect and time-to-effect concepts

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Abstract: In order to easily and systematically understand the behaviors of the various industrial systems, various system modeling techniques have been developed. Especially, the importance of system modeling technique is more emphasized in recent years since modern industrial systems become enlarged and more complex. Multilevel flow modeling (MFM) is one of the qualitative modeling techniques for the representation and reasoning about knowledge of physical phenomena and systems which cannot be modelled quantitatively. MFM can be applied to the industrial systems without additional domain-specific assumptions or knowledge, and qualitative reasoning of event causes and consequences can be conducted with high speed and fidelity. However, current MFM has a limitation that it is not able to consider dynamic features of the target system since time-related concepts are not involved. In this paper, the concepts of time-to-detect (TTD) and time-to-effect (TTE) are adopted from system failure model; and the methodology for enhancing MFM-based reasoning with time-series data is suggested. In addition, empirical TTE distribution estimation methods based on Bayesian update and non-Bayesian distribution approximation methods are described.

Keyword: Multilevel flow modeling (MFM), Time-to-detect, Time-to-effect

1 Introduction

In order to easily and systematically understand the behaviors of the various industrial systems, various system modeling techniques have been developed. Especially, the importance of system modeling technique is more emphasized in recent years since modern industrial systems become enlarged and more complex.

If the system is well-understood for acquiring analytic solutions, quantitative modeling techniques based on concrete mathematical and physical backgrounds can be applied; and phenomena within such system can be analyzed with computational approaches. However, existing systems are not always well-understood enough for applying quantitative modeling techniques, even though they involve many assumptions and simplifications. In many cases, system's internal causalities and correlations are known qualitatively rather than quantitatively, and sometimes qualitative analyses are more feasible than quantitative analyses due to practical reasons such as computation time problem.

Multilevel flow modeling (MFM) is one of the qualitative modeling techniques for the representation and reasoning about knowledge of physical phenomena and systems which cannot be modelled quantitatively. It represents the system with several interconnected levels of means and part-whole abstractions, and the goals and functions with flows (of mass, energy, and information) and their interactions[1]. Based on these characteristics, MFM can be applied to the industrial systems without additional domain-specific assumptions or knowledge, and qualitative reasoning of event causes and consequences can be conducted with high speed and fidelity.

However, current MFM has a limitation that it is not able to consider dynamic features of the target system since time-related concepts are not involved. In this paper, the concepts of time-to-detect (TTD) and time-to-effect (TTE) are adopted from system failure model; and the methodology for enhancing MFM-based reasoning with time-series data is suggested. In addition, empirical TTE distribution estimation methods based on Bayesian update and non-Bayesian distribution approximation methods are described.

The organization of the rest of this paper is as follows. Section 2 briefly explains about the characteristics of MFM and system failure model. Section 3 addresses the methodology for enhanced MFM-based reasoning with time-series data. Section 4 includes discussions about several issues emerged throughout the study. Finally, section 5 presents concluding remarks and future work outlook.

2 Preliminaries

2.1 Characteristics of MFM

MFM is a methodology for qualitative modeling of industrial processes, which represents the system's hierarchical structure with means-end and part-whole abstractions; and represents the goals and functions of the system with mass, energy, and information flows and interactions between them. MFM models are simple, but they can include many fundamental features of the target system. Fig.1 represents the basic MFM symbols including function symbols and relation symbols.

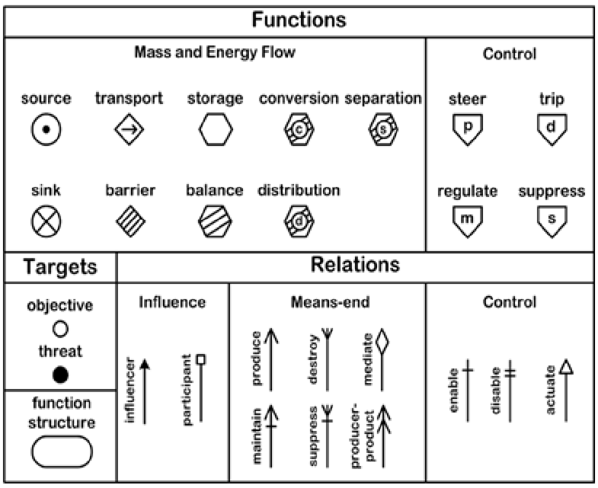

Fig.1 The basic MFM symbols[1]

Since MFM is based on fundamental laws of energy conservation and mass conservation, the whole system can be accurately modeled, and the models are easy to understand. Moreover, these characteristics also enable users to conduct qualitative reasoning, which is the process to infer causes and consequences of observed phenomena[2].

Main features of MFM can be summarized as follows.

(1) System representation with flows and interactions: MFM represents target system's functions with elementary flow and corresponding control functions to form function structures. Accordingly, most of existing systems could be modeled easily and accurately without additional domain-specific assumptions or knowledge.

(2) Qualitativeness: Since MFM is one of the qualitative modeling methodologies, system can be modeled without detailed quantitative relations and therefore easy to apply for most of systems. However, application of MFM would not suitable if quantitative modeling is available or required.

(3) Model-based reasoning: Reasoning with MFM is based on pre-defined models. Once models are established, additional empirical data is not considered during reasoning processes unless models are revised.

(4) Snap-shot evidences and results: Since current MFM does not involves the concept of time, it is not able to consider time-related issues and accordingly not able to consider dynamic features of the systems. During the cause reasoning, it is not available to aggregate serial observations and therefore it is needed to repeatedly conduct cause reasoning for every updated observation. During the consequence reasoning, it is able to infer that which event will 'eventually' happen, but not able to infer 'when' will it happen.

Among these features, the last feature (4th) is regarded as one of the main drawbacks of MFM, since in many cases, time-related data is utilized for cause and consequence reasoning as valuable evidence. Order of the event occurrence or time-gap between the event occurrence can be regarded as the crucial evidences for reasoning.

If MFM becomes capable to consider dynamic features, it is expected that more delicate cause reasoning would be possible since time-related data can be considered as new evidence, and more detailed consequence reasoning would be possible including the information about when the 'event-in-interest' happens.

2.2 System failure model

System failure model (tentative name) was suggested as one of the core concept of functional fault analysis (FFA). FFA is a systematic design methodology which for the integration of system health management (SHM) concept to the early design stage of complex systems such as spaceships, based on high-level functional model of the system that captures the physical architecture[3].

Among the various concepts of FFA, system failure model was established in order to consider the propagation of the effects of various failure modes and the timing by which fault effects propagate along the modeled physical paths.

Accordingly, system failure model involves various timing definitions. These timing definitions are represented in Fig.2.

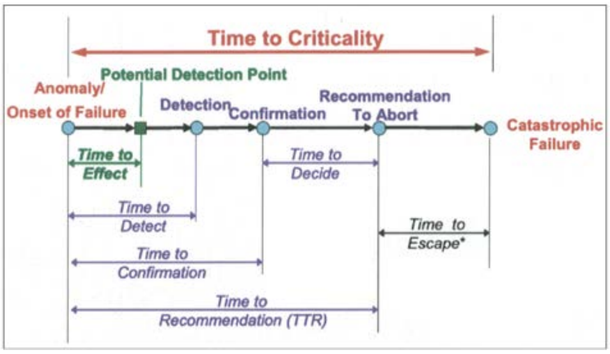

Fig.2 Schematic of system failure model and its timing definitions[3]

However, system failure model was established specifically for the spaceship cases, and therefore minor modification on the model should be applied in order to grant generality. The modified system failure model for general industrial systems is represented in Fig.3, and corresponding timing definitions are as follows.

(1) Time-to-effect (TTE): The time from the 'onset of failure' to the point when its effects are potentially detectable.

(2) Time-to-detect (TTD): The time from the 'onset of failure' to the confirmation of the fault existence.

(3) Time-to-diagnosis: The time from the 'onset of failure' to the identification of the fault (e.g. fault location, fault type, etc.).

(4) Time-to-mitigation: The time from the 'onset of failure' to the complete prevention of the critical system failure.

(5) Time-to-criticality: The time from the 'onset of failure' to the critical system failure.

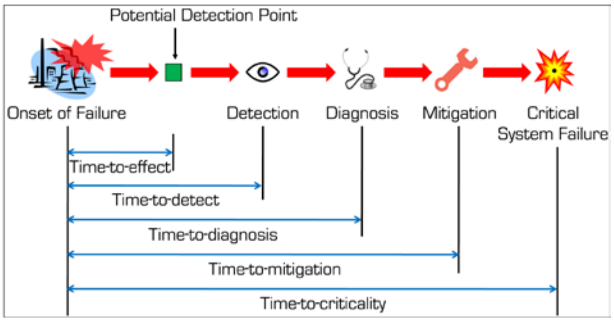

Fig.3 Schematic of modified system failure model and its timing definitions

3 Application of TTD and TTE Concepts to MFM

The concepts introduced in modified system failure model were applied to MFM in order to make MFM to be capable of time-related issues. In this section, the processes for the application are addressed.

3.1 Modified definitions of TTD and TTE in MFM's perspective

MFM based reasoning is conducted for the cases when one or more functions are not-in-normal states, which include failed states. Therefore, it is needed to re-define the timing definitions from modified system failure model in MFM's perspective in order to adopt such concepts to the MFM.

Among various timing definitions, only TTE and TTD are relevant to the MFM. The other timing definitions are neglected since they are related to the processes of diagnosis and mitigation of failure, which are out of MFM's scope.
Let's consider that there is a simple system with only two interconnected functions (function A and function B; function A affects function B), and corresponding instrumentation systems (instrumentation system A and instrumentation system B). This system can be represented as Fig.4. MFM usually do not represent instrumentation systems but they are shown for better understanding.

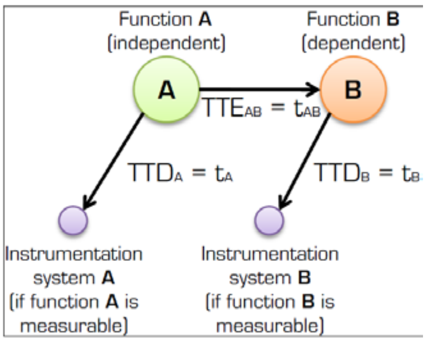

Fig.4 Diagram for simple two-function system

If function A's state is measured, TTD for function A can be re-defined as; the time from the 'actual state alteration of function A' to the point when 'detection of state alteration of function A'. Similarly, TTE between function A and function B can be re-defined as; the time from the 'actual state alteration of function A' to the point when it induces 'actual state alteration of function B'. Here, the word 'actual' is used in order to discriminate the detection of state alterations from the real state alterations.
These concepts could be applied to any MFM models since every function node in MFM model with corresponding instrumentations would have its own TTDs and every influence relation between function nodes in MFM model would have its own TTEs.

3.2 Estimation of TTDs and TTEs

In section 3.1, TTD and TTE concepts are adopted and defined in MFM's perspective, and these concepts can be applied to general MFM models without difficulties. However, it lays another practical question; *how to estimate TTDs and TTEs?*
In case of TTDs, most of the instrumentation systems are both theoretically and empirically well-defined, and that kind of instrumentation systems would be applied to the real-world systems. Therefore, issues related to the estimation of TTDs are not considered in this paper.
However, estimation of TTEs are expected to be much harder than that of TTDs because of several reasons.

(1) If the system is well-understood for solving differential equations, TTEs could be estimated analytically. However, MFM would not be applied to such system.
(2) In most cases, multiple functions are serially connected while instrumentation systems do not. This imposes complexity of analysis.
(3) There are many kinds of factors that affect TTE, including state thresholds, input conditions, and causes of single function's state alterations. Accordingly, it is hard to generalize TTEs.

With considering these difficulties, empirical TTE estimation methods are addressed. Specifically, in section 3.2.1, method for empirical estimation of TTEs based on Bayesian update is presented, and in section 3.2.2, method based on non-Bayesian probability distribution approximation is presented. These two methods have difference whether it defines the form of prior and posterior distributions or not.

3.2.1 Estimation of TTEs based on Bayesian update

Bayesian update, also widely known as Bayesian inference is one of the methods of statistical inference which can be used to update the probability for a hypothesis based on newly obtained evidences. With its concrete mathematical background, namely Bayes' theorem, Bayesian update has been served as useful and reliable method for approximating true distribution of population from the sample.

Equation for the Bayesian update can be represented as follows.

$$P(\theta \mid Data) = \frac{P(Data \mid \theta)}{P(Data)} \cdot P(\theta) \qquad (1)$$

If the hypothesis is represented as probability distribution, it is needed to define the form of prior and posterior distribution. If the event propagation from function A to function B is observed for *k* times, TTE distribution can be obtained through *k* times of update.

Bayesian updating processes are highly affected by the forms of prior and posterior distributions. Beta distribution is one of the widely used as prior and posterior distributions since it can represent many other kinds of distributions approximately.

However, not only beta distribution but also many other kinds of commonly used distributions are not suitable for representing multimodal distributions (distributions with multiple peaks). Accordingly, although multimodal distributions frequently emerge in real-world data, it is hard to consider multimodal distributions with Bayesian update. Many studies have been conducted to solve multi-modality problem in Bayesian update, but it is still on-going and not perfectly solved[8][9].

3.2.2 Estimation of TTEs based on non-Bayesian probability distribution approximation

As mentioned, commonly used distributions are not suitable for representing multimodal distributions since it is hard to represent various multimodal distributions in general formula. Instead, most of multimodal distributions are expressed as linear combinations of multiple unimodal distributions, and it makes Bayesian update hard to consider multimodal distributions.

Alternatively, studies on non-Bayesian approaches for approximation of multimodal distributions have been actively conducted, which do not require definitions on the forms of prior and posterior distributions[4-7]. Although these studies are still on-going and none of them guarantee that they could be applied well for any type of multimodal distribution, many non-Bayesian probability distribution approximation methods are more capable for multimodal distributions than Bayesian update.

If the event propagation from function A to function B is observed for *k* times, TTE distribution can be obtained simply through merging all evidences and applying approximation algorithm.

However, in order to apply non-Bayesian probability distribution approximation algorithms, relatively large number of observation is needed since there is no prior information about the form of distribution.

3.3 Probabilistic reasoning based on TTD and TTE distributions

If TTD and TTE distributions are sufficiently estimated, it is able to conduct more detailed cause and consequence reasoning than conventional MFM. This section describes how advanced probabilistic reasoning can be conducted based on estimated TTD and TTE distributions.

In order to conduct reasoning processes based on TTD and TTE distributions, it is needed to consider the summation of two or more TTD and TTE distributions. If it is assumed that distributions are independent to each other, this problem can be regarded as the summation of distributions of independent random variables, which is solvable through convolution.

The probability distribution of the sum of two or more independent random variables can be calculated by applying convolution operator to their individual distributions. For the continuously distributed random variables with probability density functions *f* and *g*, general formula for the distribution of the sum $Z=X+Y$ is as follows.

$$h(z) = (f * g)(z) = \int_{-\infty}^{\infty} f(z-t)g(t)dt \qquad (2)$$

In section 3.3.1 and 3.3.2, probabilistic cause and consequence reasoning based on estimated TTD and TTE distributions are described.

3.3.1 Probabilistic cause reasoning

To simplify the problem, let’s assume that there are two event paths (cause suspects) which can affect both function A and function B. Since two event paths involve different functions, their TTD and TTE profiles would also be different. In this case, distribution of the time-gap between ‘detection of function A’s state alteration’ and ‘detection of function B’s state alteration’ can be obtained for each event path through series of convolution operations.

After the time-gap distribution for each event path is obtained and actual time-gap is observed, it is able to calculate the probabilities of event occurrence due to event path 1 and event path 2. If we denote the actual time-gap as $\mathbf{t_m}$ and time-gap distribution for event path 1 and event path 2 as $\mathbf{pd_1}$ and $\mathbf{pd_2}$ respectively, probabilities of event occurrence due to event path 1 (P_1) and event path 2 (P_2) can be calculated as follows.

$$P_1(t=t_m)=\frac{pd_1(t_m)}{pd_1(t_m)+pd_2(t_m)} \tag{3}$$

$$P_2(t=t_m)=\frac{pd_2(t_m)}{pd_1(t_m)+pd_2(t_m)} \tag{4}$$

Upper equation can be generalized for multiple (larger than two) event path cases. If there are n possible event paths, probability of event occurrence due to event path x (P_x) can be calculated as follows.

$$P_x(t=t_m)=\frac{pd_x(t_m)}{\sum_{k=1}^{n} pd_k(t_m)} \tag{5}$$

3.3.2 Probabilistic consequence reasoning

To simplify the problem, let’s assume that function A’s state alteration is observed and it can induce function B’s state alteration. If TTD distributions for function A and function B are well-defined, and TTE distributions between function A and function B are well-defined, time-gap distribution between ‘detection of function A’s state alteration’ and ‘detection of function B’s state alteration’ can be easily calculated through series of convolution operations. Calculated time-gap distribution itself implies when function B’s state alteration will be detected, which is an advanced consequence reasoning.

If new observation about specific function’s state alteration between function A and function B become available, time of function B’s state alteration detection can be predicted with reduced uncertainty.

4 Discussion

In this section, several issues emerged throughout the study are discussed.

4.1 Dilemma of MFM improvement

MFM’s main characteristics such as simplicity and qualitativeness can be regarded as both advantages and disadvantages. In the perspective of applicability, these are definitely advantages. However, at the same time, they are disadvantages in the perspective of precision. This is why simplicity and qualitativeness of MFM are regarded as characteristics rather than advantages or disadvantages.

Thus, improvement of MFM should be conducted with no-harm to MFM’s own characteristics. However, this is a dilemma since both advantages and disadvantages are based on same characteristics, meaning that eliminating the disadvantages could induce elimination of advantages.

MFM can abstract various systems into the general flows of mass and energy, but not including the physical properties of them. Therefore, in order to quantify MFM, it is needed to implement domain specific information, which may harm the baseline characteristics of MFM.

Alternatively, in order to quantify MFM with avoiding serious harm to its own characteristics, the only variable which can be applied equally to every system was quantified in this study, namely time.

4.2 Empirical TTE estimation

Since quantitative calculations based on system’s specific characteristics are not available, empirical methods including Bayesian and non-Bayesian approaches for TTE distribution estimation were considered in this study. By selecting empirical approaches, it is able to estimate TTE distributions based on observed data and accordingly not seriously harm MFM's simplicity and qualitativeness.

Unfortunately, estimation of TTE distributions based on Bayesian update is highly dependent to prior and posterior probability distribution models. It is an undoubtedly effective tool for hypothesis verification, but this high dependency leads to its lack of capabilities on multimodal distributions.

Estimation of TTE distributions based on non-Bayesian probability distribution approximation methods could solve the multi-modality problems, but requires more data for reliable analysis. It would be a serious obstacle for real-world applications of MFM.

However, it is not necessary to choose only one approach for TTE distribution estimation. Mixed approach can be considered which applies Bayesian update when the amount of data is small, and applies another method when the data is sufficiently collected. Alternatively, if it is expected that the target TTE distribution is unimodal, continuous application of Bayesian update can be considered.

As empirical approaches are inevitably highly dependent to observed or measured data and its uncertainty, quality of the collected data should be sufficiently high, and its uncertainty should be defined precisely.

4.3 Relation between TTEs and event modes

Previously mentioned probabilistic cause reasoning reveals which event path (including multiple functions) was induced observed phenomena with probabilities. In the other word, the resolutions of reasoning processes are the single function, implies that it is not able to know why abnormality happens to initial function. However, if following assumptions are valid, it would be able to conduct more detailed probabilistic cause reasoning, which reveals why initial function's abnormality happens (i.e. event mode).

(1) TTE distributions for specific event modes are unimodal.

(2) TTE distributions for specific event modes have distinctive peaks to each other (i.e. sufficiently separable).

(3) For each event mode, the probability of occurrence is sufficiently high to observe.

If these assumptions are valid, specific function's whole TTE distribution would be a multimodal distribution which can be decomposed into multiple unimodal distributions clearly, and then it would be able to infer which event mode induced abnormality for that function from the observed TTE, similar to the mentioned probabilistic cause reasoning process.

However, not only validities of the assumptions should be checked but also relation between TTE and event modes should be revealed through additional analyses. Moreover, it is needed to consider the possibilities of having different TTEs for different input conditions (for same event mode) or having similar TTEs for different failure modes.

Since this issue is beyond the scope, it will be not addressed in detail. Additional works on this issue should be conducted as future work.

5 Conclusion

In this paper, concepts of TTD and TTE were adopted from the modified system failure model in order to grant the capability for dynamic features to MFM. Additionally, empirical methods for actual TTD and TTE distribution estimation and advanced probabilistic reasoning based on estimated TTD and TTE distributions were introduced.

Regarding empirical TTE distribution estimation, both Bayesian update and non-Bayesian probability distribution approximation methods have their own advantages and disadvantages. Bayesian update is data-efficient, but has limitation on considering multimodal distributions. Non-Bayesian methods can solve multi-modality problems, but relatively data-inefficient. It would be better to consider mixed approach in order to emphasize each method's advantages and offset each other's disadvantages.

Studies on multimodal distribution approximation and decomposition methods have been conducted, but none of them guarantee that they could be applied well for any type of multimodal distribution. Also for Bayesian update, studies to solve multi-modality problem are still on-going. Since mathematical and computational backgrounds of proposed methods are not perfect for practical applications but greatly affect the quality of TTE distribution estimation, it is needed to continuously check the related researches for the application of suggested concepts to MFM.

It is expected that MFM's applicability to various systems could be enhanced with the contents of this study, since more evidences become available while conducting reasoning processes compare to the conventional MFM. Especially, this kind of enhancement would be more emphasized for the systems with sparse instrumentation systems.

As future works, it is needed to conduct case studies for the examination of practical applicability of suggested concepts and methods, and continuous monitoring on underlying algorithms should be conducted. Additionally, it would be meaningful to conduct studies on more detailed probabilistic cause reasoning for single function's event modes.

Acknowledgement

This research was supported by the National R&D Program through the National Research Foundation of Korea (NRF) funded by the Korean Government. (MSIP: Ministry of Science, ICT and Future Planning) (No. NRF-2016R1A5A1013919)

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