CURRENT DIAGNOSTICS OF THE EVAPORATION STATION

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Abstract: The paper presents structure and algorithms of the system of current diagnosis of the evaporation station in the Lublin Sugar Factory. The applied fault detection algorithms are based on the set of partial parametric models, the set of heuristic dependencies describing process behaviour and the hardware redundancy. The isolation algorithm implements fuzzy reasoning based on the diagnostic rules given by the expert. All the diagnostic algorithms are carried out by the modules of Advanced Monitoring and Diagnostic System AMandD. The achieved fault detectability and isolability analysis and some test results are also presented.

Keywords: implementation, diagnostic programs, diagnostic inference, fuzzy logic, fuzzy modelling, supervision.

1. INTRODUCTION

Currently available functions of process supervision, controll and monitoring systems (SCADA, DCS) are relatively limited. Typical sollutions are focused on: visualisation of process variables and process trends, alarms detection and management, calculation of statistical and brief indexes describing process behavior, reporting, etc. Such a way of process supervision can be threated as a basic supervision. Recently created systems provide more tools (available in a form of system modules or as an external software components) for advanced process supervision tasks such as:

- process modelling,
- virtual sensors and analysers,
- software redundancy and process variables reconstruction for faulty measurements,
- model based prediction of process variables / process behaviour,
- fault detection (for components, sensors and actuators),
- fault isolation
- operators support in abnormal / faulty state.

Most of the above mentioned functions can be implemented by use of Advanced Monitoring and Diagnostic System AMandD. This system was developed in the Institute of Automatic Control and Robotics, Warsaw University of Technology, during the European Union project called *Advanced decision support system for Chemical/Petrochemical manufacturing processes - CHEM.* AMandD system is a unique system that combines several up-to-date techniques for system modelling and diagnosis. It can be applied, among others, in petrochemical, chemical, power, food and metallurgical industries. This paper describes the implementation of the above system for the diagnosis of the evaporation station in sugar factory.

2. DIAGNOSED PROCESS

The diagnosed process is an evaporation station. This is a part of the technological installation for sugar manufacturing, where the densification of thin sugar beet juice takes place. The evaporation station is divided into five sections. The first three are supervised by the considered diagnostic system. Exemplary, the first section (Fig. 1) consists of a buffer tank, four superheaters and first evaporator. Twins sections, second and third, consist only of two evaporators.

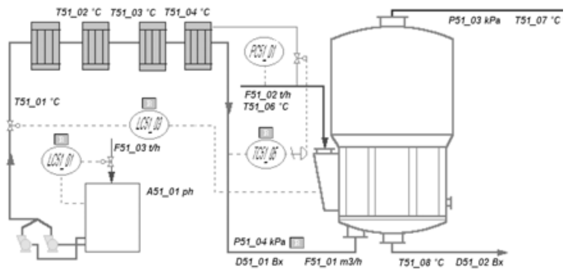

Fig. 1. First section of evaporation station.

There are about 150 measured process variables (temperatures, levels, pressures, densities, etc.) in the whole installation. Process operation is leaded by PLC controllers. Visualisation is available by the use of SCADA system. Sampling rate for each measurement is equal to 10 seconds. Up to now, there is no diagnostic system available in the sugar factory. Only standard alarm controlling is performed.

The whole installation was divided into and described by a tree structure for the diagnostic system purposes. The two top levels of the structure are presented in Table 1. The names of diagnostic tests and possible faults were created according to that structure. The heaters section (SW.1.3) is used in this paper as an example.

Table 1: Two top levels of the process decomposition.

Level 1: Section	Level 2: Area
SW.1 Section 1	**1** – Buffer tank ZB **2** – Flow control FC **3** – Heaters area **4** – Evaporator AW1
SW.2 Section 2	**1** – Evaporator AW2A **2** – Evaporator AW2B
SW.3 Section 3	**1** – Evaporator AW3A **2** – Evaporator AW3B

Table 2: The set of faults for heater section (SW1.3)

Symbol	Description
f-SW.1.3.1.1s	Sensor fault T 51.01
f-SW.1.3.1.2s	Sensor fault T 51.02
f-SW1.3.1o-1	Heater no 1 fault
f-SW.1.3.2.1s	Sensor fault T 51.03
f-SW.1.3.2o-1	Heater no 2 fault
f-SW.1.3.3.1s	Sensor fault T 51.04
f-SW.1.3.3.o-1	Heater no 3 fault
f-SW.1.3.4.1s	Sensor fault TC 51.05
f-SW.1.3.4.2a	Actuator fault TC51.05
f-SW.1.3.4.3s	Sensor fault T51.06
f-SW.1.3.4.4s	Sensor fault P51.01
f-SW.1.3.4.5s	Sensor fault F51.02
f-SW.1.3.4.6c	Improper operation of TC51.05 controller
f-SW.1.3.4.7c	Improper operation of PC51.01 controller
f-SW.1.3.4o-1	Heater no 4 fault
f-SW.1.3.4.p-4	Too high juice temperature
f-SW.1.3.4.p-5	Too low juice temperature
f-SW1.3.4.p-2	Unexpected change of heating steam temperature
f-SW1.3.4.p-3	Unexpected change of heating steam pressure or luck of medium

The set of considered faults was defined based on installation description, expert knowledge and industrial practise. This set includes faults of measurement paths (marked as 's'), actuators (a), technological devices (o) and incorrect process states (p). The list of possible faults for the heaters section is presented in Table 2.

3. DIAGNOSTIC ALGORITHMS

The scheme of the applied diagnostic algorithms is presented on Figure 2. First, the residual values r_j are calculated based on the set of process variables P analysis. Then, fuzzy evaluation of residuals gives a set of diagnostic signals S_j. Each diagnostic signal is a qualitative representation of corresponding residual signal. The set of diagnostic signals S is analysed on the basis of diagnostic relation R^{FS} introduced to the system during the configuration stage. Finally, fuzzy inference is used to conclude about the existing faults in the system. The diagnosis is formulated as a set of fault certainty factors f_k.

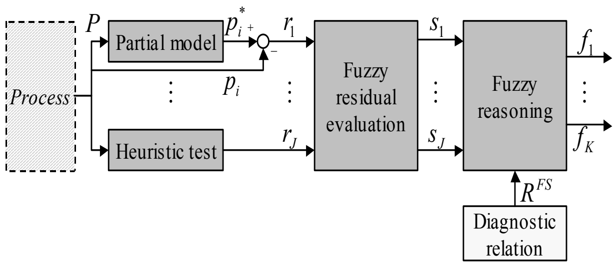

Fig. 2. Diagnostic algorithm structure.

3.1. Diagnostic tests

The diagnostic tests used in the detection algorithms are based on the relations between process variables *(Korbicz, et al, 2004)*. In general, about 160 diagnostic tests were designed. They can be divided into seven categories:

- Tests that detect measuring paths faults (marked with symbol 'W'). They monitor characteristic signal parameters like possible range and speed of change. They also detect decay of the signal variability
- Tests based on detection of exceeding the alarm limits (marked with A). Those tests, in many cases, duplicate classic alarm system implemented in SCADA.
- Tests based on hardware redundancy (marked with symbol 'R'). These tests relay on calculating the differences between the measurements of the same physical variable realised by two different sensors. For example, the redundant sensors are used to measure the juice level in the evaporators (controlling the level of the juice is a crucial task in respect to safety conditions). One of the sensors is used in a control-loop while the second one has only the information character.

- Check of the control loops (marked with symbol 'C'). This tests monitor control deviation, correctness of the control algorithms operation and detects loose of controllability.
- Tests based on simple heuristic relations between variables (marked with symbol 'K'). One can find several simple, invariant in time dependences among process variables. They can be determined based on expert knowledge about the process, equipment elements specification and analysis of the archival data sets. Such dependences are constant unless the fault appeared in the system. As an example, such relation can be found between juice temperatures in the evaporator sections.
- Tests based on the partial parametric models (marked with symbol 'M'). The redundant process variables are reconstructed based on partial parametric models. Then, the differences between reconstructed and real process variable values are calculated. The applied partial models are described in Section 3.2.
- Check of the actuators switch-on signals and control loops parameters (marked with symbol 'S').

The diagnostic tests used in the described application cover almost whole process. In Table 3 the part of set of tests defined for the heaters section is presented.

Table 3: Chosen diagnostics tests for the heaters section (SW1.3).

Notation	Draft of algorithm	Short description
s-SW.1.3.4.4s-1W	$[STD(PC51.01) > \Delta_1]$ $[\min_{PC51.01} < PC51.01 < \max_{PC51.01}]$ $[\Delta PC51.01/\Delta t < \Delta_3]$	Detect the PC51.01 measuring paths faults
r-SW.1.3.4-1A	$(C_{T51.06} - T51.06) < \Delta$	Check of the heating steam temperature
s-SW.1.3.4-2C	if [(TC51.05.SP - C51.05.PV) > Λ and (TC51.05.CV <> 100)] then (↑ TC51.05.CV) if [(TC51.05.SP - TC51.05.PV) <Λ and (TC51.05.CV <> 0)] then (↓ TC51.05.CV)	Check of the TC51.05 control loops

s-SW.1.3.4-3C	if (TC51.05.CV =100)
	then (↑ TC51.05.PV)
	if (TC51.05.CV =0)
	then (↓ TC51.05.PV)
		Detects loose of controllability in the TC51.05 control loops

r-SW.1.3.1-1K	$T51.02 - T51.01$	Check of the juice temperature increase in heater I
s-SW.1.3.4-1M	$TC51.05.PV +$ $- f(T51.04, TC.51.05.CV)$	Check of the juice temperature increase in heater IV

3.2. Partial models of selected subsystems

There is no analytical model of the whole evaporation station available till now. To generate residuals there was a need to prepare a set of parametric models that covers selected subsystems. The following subsystems were chosen to be modelled:

- Flow of the juice (signal F51.01). In fact this is a model of a control valve. As an input to the model the control value (CV) and the juice pressure were used.

$$\mathrm{F51.01} = \mathrm{f}(\mathrm{LC51.03CV}, \mathrm{P51.04}) \tag{1}$$

Another possibility is to build simplified model, without taking into account the juice pressure.

- Temperature of the juice after the heater IV. As an input to the model the juice temperature before the heater and the control signal of the amount of heating steam were used.

$$\mathrm{TC51.05.PV} = \mathrm{f}(\mathrm{T51.04}, \mathrm{TC51.05.CV}) \tag{2}$$

- Set of temperature-pressure relations in the consecutive evaporators. The temperature and the pressure of the outlet steam in each evaporator are correlated.

$$\mathrm{T51.07} = \mathrm{f}(\mathrm{P51.03}) \tag{3}$$

$$\mathrm{T52.01} = \mathrm{f}(\mathrm{P52.01}) \tag{4}$$

$$\mathrm{T54.01} = \mathrm{f}(\mathrm{P54.01}) \tag{5}$$

The mentioned model equations have unknown structure and are nonlinear. Identification procedure was used to receive appropriate models. Because of nonlinearity of the subsystems, there was no possibility to use classic linear transfer functions.

Fuzzy models are very effective for approximation of static characteristic as well as dynamics for uncertain nonlinear systems. In literature different modeling techniques can be found. Among them, Takagi-Sugeno-Kanga (TSK) model structure has attracted a lot of attention (Takagi and Sugeno, 1985). This model consists of rules with fuzzy antecedents and mathematical function in the consequent part. Usually conclusion function is in form of dynamic linear equation. Each rule takes the following form:

$$\mathrm{R_i} : \mathrm{if}\left[\mathrm{x_1} = \mathrm{A_i^1} \wedge \ldots \wedge \mathrm{x_n} = \mathrm{A_i^n}\right] \mathrm{then}\left[\mathrm{y} = \mathrm{f_i}(\mathrm{u})\right] \tag{6}$$

where: R_i- i^{th} rule, x_j - j^{th} fuzzy input, ($j=1,2,\ldots,n$), A_i^j - j^{th} partition in i^{th} model rule, n - number of fuzzy inputs, y - model output, f_i - consequent function for i^{th} rule, u - consequent function parameters vector.
Fuzzy antecedents of those rules divide input space into a specified number of fuzzy regions. Each partition is defined by its membership function. In this case a normalized triangle was used as a membership function shape:

$$\mu(\mathrm{x}) = \max\left(0, \min\left(\frac{\mathrm{x}-\mathrm{a}}{\mathrm{b}-\mathrm{a}}, \frac{\mathrm{c}-\mathrm{x}}{\mathrm{x}-\mathrm{b}}\right)\right) \tag{7}$$

while assuming that $a \le b \le c$ and the parameters of the successive membership functions are related according to the following formula:

$$\forall \mathrm{i} \quad \mathrm{a_i} = \mathrm{b_{i-1}} \wedge \mathrm{c_i} = \mathrm{b_{i+1}} \,. \tag{8}$$

The most popular form of the function f_i in the rule consequents is a linear differential equation of the form:

$$f_i(u) = a_0^{(i)} + a_1^{(i)} u_1 + .. + a_m^{(i)} u_m \qquad (9)$$

where: $a_j^{(i)}$ - j^{th} equation coefficient of i^{th} rule conclusion, u_i - input vector given as $u=[u_1,u_2,\ldots,u_m]$, $u \in R^m$ consisted of delayed input signals values.

All the models were identified by the use of MITforRD software (modelling tool for the AMandD system). This software allows to carry through the full identification process and to search automatically for model structure (in sense of determination the number and the parameters of the fuzzy partitions as well as the consequent function form). During the identification process the evolutionary algorithm proposed by Wnuk (2004) for model structure search was used. The coefficients of linear consequent functions were estimated using LS (Least Square) method. The accuracy of received models was in the range 0.2 up to 1.2 % of the process variable range. Exemplary modelling validation result for model of the temperature after the heater IV in the heaters section (SW.1.3) is presented on Figure 3.

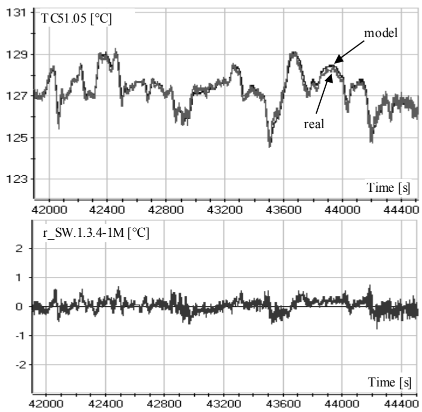

Fig. 3: Modelling quality for the model of the temperature after the heater IV. Average modelling accuracy: 0.23 % of the process variable range. Top figure shows the comparison of the real process variable and model output time series, while the bottom one shows modelling error.

3.3. Diagnostic reasoning

In the case of all the residuals the three-valued fuzzy evaluation has been applied (Frank, 1994; Kościelny and Syfert, 2003b). For each residual only one fuzzy set 'Z' describing its values in fault free state has been attributed. Two other fuzzy sets describe residual values in fault states. The set 'N' covers values smaller, and the set 'P' values greaten than those in normal state. The sets 'P' and 'N' are called fault symptoms because their appearing testifies about existence of one of the faults in the process.

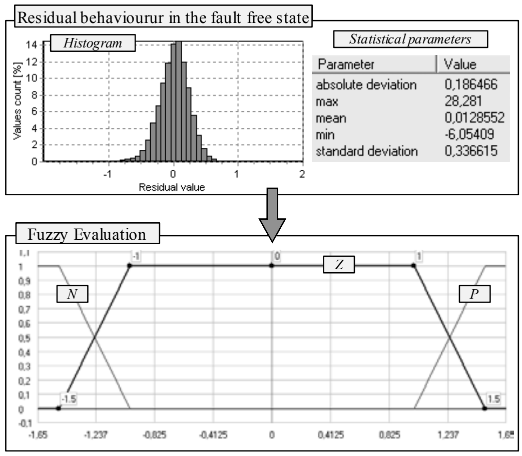

Fig. 4: An example of selection of fuzzy evaluation parameters of the residual r-SW.1.3.4e-m.

The parameters of the membership functions of 'Z', 'N' and 'P' fuzzy sets were tuned based on the statistical parameters of residual time series recorded during fault free operation. An example of such a selection in shown on Fig. 4. The parameters of the Z membership functions were setup automatically in the following way: the width and the position of the Z set was set according to 6 x standard deviation and mean value, the fuzzy region was set as 25% of Z set width. The sets P and N were set as complement of the Z set. Than, some of the parameters were changed by the expert.

The algorithm Industrial - Dynamic Table of States (I-DTS) (Kościelny and Syfert, 2003a) has been applied for fault isolation. Its basic features can be summarised as:

- Two-level hierarchical structure of the algorithm. There is a possibility for introducing system decomposition.
- Ability of detecting system states that were not considered during configuration.
- Implementation of the serial-parallel inference (modification of the methods TDS, F-DTS, and T-DTS (Korbicz, *et al*, 2004)).
- Dynamic creation of isolation threads. It increases the ability to isolate multiple faults.
- Different kinds of uncertainties and the symptoms dynamics can be taken into account.
- Correction of reasoning mechanism is applied (automatic adaptation) in the case of varying the set of available measurements.
- Possibility of easy system extension during exploitation.

The static decomposition of the isolation algorithms in two-level hierarchical structure has been used. On the top level, the process has been divided into three main, independently diagnosed global sections that correspond to the consecutive sections of the process (SW.1, SW.2 and SW.3). Additionally, the first global section SW.1 has been divided into four subsections on the bottom level of the hierarchical decomposition (sub-processes SW.1.1, SW.1.2, SW.1.3 and SW1.4). The division of the diagnostic process applied during the static decomposition corresponds to the sections of the process defined during its analysis and presented in Table 1.

The relation between the faults and observed symptoms (diagnostic relation) has been declared based on the expert knowledge about the process and the knowledge about the structure of available residuals. Table 4 presents exemplary part of diagnostic matrix for the heaters section (SW.1.3). Table 6 presents the summary of achieved fault detectability and isolability for particular sub-processes while Table 5 presents exemplary detailed analysis for the heaters section (SW.1.3).

Table 4: Exemplary part of diagnostic matrix for the heaters section (SW.1.3).

	s-SW.1.3.1-1K	s-SW.1.3.2-1K	s-SW.1.3.3-1K	s-SW.1.3.4-1M	s-SW.1.3.4-1C	s-SW.1.3.4-1A	s-SW.1.3.4-2A
f-SW.1.3.1.1s	N;P						
f-SW.1.3.1.2s	N;P	N;P					
f-SW1.3.1o-1	N;P						
f-SW.1.3.2.1s		N;P	N;P				
f-SW.1.3.2o-1		N;P					
f-SW.1.3.3.1s			N;P	N;P			
f-SW.1.3.3o-1			N;P				
f-SW.1.3.4.1s				N;P	N;P		
f-SW.1.3.4.2a				N;P			
f-SW.1.3.4.3s						N;P	
f-SW.1.3.4.4s							N;P
f-SW.1.3.4.5s							
f-SW.1.3.4.6c					N;P		
f-SW.1.3.4.7c							
f-SW.1.3.4o-1				N;P			
f-SW.1.3.4.p-4					P		
f-SW.1.3.4.p-5					N		
f-SW1.3.4.p-2				N;P		N;P	
f-SW1.3.4.p-3				N;P			N;P

Table 5: Exemplary fault detectability and isolability for heaters section (SW.1.3).

Section SW.1.3	Faults		
Isolable faults	f-SW.1.3.1.2s	f-SW.1.3.3.1s	f-SW.1.3.4.1s
	f-SW.1.3.2.1s	f-SW.1.3.4.3s	f-SW1.3.4.p-2
	f-SW.1.3.2o-1	f-SW.1.3.4.4s	f-SW1.3.4.p-3
Conditionally isolable faults	(f-SW.1.3.4.6c - f-SW.1.3.4.p-4)		
	(f-SW.1.3.4.6c - f-SW.1.3.4.p-5)		
Unisolable faults	(f-SW.1.3.1.1s - f-SW1.3.1o-1)		
	(f-SW.1.3.4.2a - f-SW.1.3.4o-1)		
Undetactable faults	f-SW.1.3.4.5s		

Table 6: Summary of achieved fault detectability and isolability.

Decomposition level		Isolable faults	Conditionally isolable faults	Unisolable faults	Undetactable faults
Top	Bottom				
SW.1	SW.1.1	4	0	4	2
SW.1	SW.1.2	4	0	6	0
SW.1	SW.1.3	9	3	2+2	2
SW.1	SW.1.4	8	2	2	7
SW.2	-	8	6	6	0
SW.3	-	8	6	6	0

4. DIAGNOSTIC SYSTEM STRUCTURE

Diagnostic task is realized by AMandD system modules. The whole system was developed as a part of CHEM project realized in EU 5 Framework Programm. The simplified structure of the system is presented on Fig. 5.

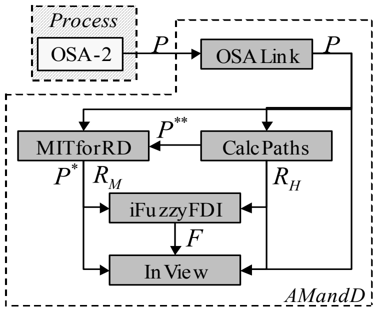

Fig. 5. Modules of the diagnostic system AMandD.

The process variables are taken from SCADA system OSA-2 through specialised input-output software module called OSALink. Then, the current values of the process variables P are delivered to two calculation modules:

- CalcPaths is a module that makes different process variables calculations in the way similar to Matlab-Simulink environment. It calculates heuristic diagnostic test results R_H (all the tests mentioned in Section 3.1. except model based residuals) and some additional calculated variables P** needed by MITforRD.
- MITforRD module is responsible for calculation of the outputs of partial parametric models. The set of reconstructed process variables P* as well as the subset of residuals values R^M are calculated here.

Residual values are delivered to the third calculation module called iFuzzyFDI. This module is responsible for fuzzy evaluation of residuals and diagnostic inference. Final conclusion is elaborated as a set of fault existence certainty factors F. All processed variables are delivered to visualisation module InView, which is an operator interface for the diagnostic system.

5. TESTS OF THE SYSTEM

The example of heater fault diagnosis is presented in this section. Figure 6 presents the time series of the process variables related with faulty component. One can notice a time period, in which, the temperature gradient on the heater I (T51.02 – T51.01) significantly decreased. The changes of temperature gradients on other heaters did not exceed acceptable limits. The observed process disturbance was caused by switching of the first heater. The diagnostic system pointed out the group of two unisolable faults: the T51.01 sensor faults and heater I fault. The time series of these fault certainty factors are presented on Figure 7.

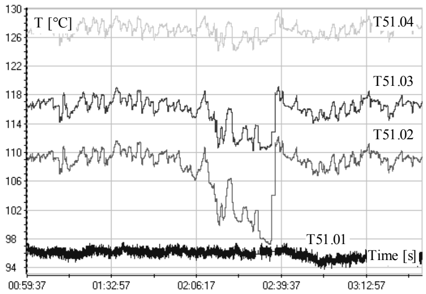

Figure 6: Process variables connected with the juice heaters.

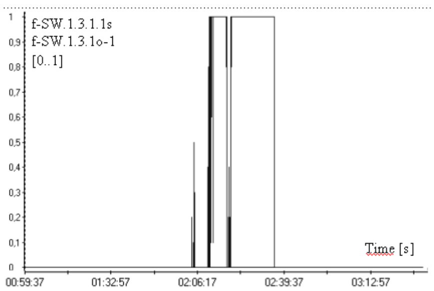

Figure 7: Certainty factors of the faults pointed out in the diagnosis.

6. SUMMARY

The system had to be configured with use of process data from normal operation. The use of the data from previous years was limited according to the changes in the process structure as well as due to the limitations of data export from SCADA system. Because of this, the system reached its full usefulness at the end of the campaign, which lasted about two months.

During defining the diagnostic relation, the experts assumed full efficiency of the process. When the system started to operate it pointed out several faults, mainly of the density measurement paths. This diagnosis confirmed the knowledge already possessed by the operators. This preliminary confirmed proper configuration and operation of the diagnostic system. They the system was reconfigured because there was no possibility to repair these faulty components. After this, the system did not indicate any faults, it started its normal operation.

During the short period, when the system was operating, nothing important happed. Presented fault detection and isolation exampled (Section 5) was reconstructed with use of process data from the beginning of the campaign. The diagnostic test algorithms were design in that way, to work properly during next campaigns. Because of existing process repairs between the campaigns, maybe there will be a need for slight tuning during first days of the next campaign. Thus, the entire next campaign will be supervised by AMandD system.

Due to the character of the evaporation station (high possibility of installation pollution caused process stop, danger of the evaporator explosion, etc.) and relatively short installation operation period the operators think that application of diagnostic system AMandD should result in:

- increasing the process safety due to fast and precise information about emerging faults,
- decreasing the hazard for the environment,
- lowering of losses in faulty states (they are usually huge),
- elimination of operators information overloading.

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