Model-Based Diagnosis for Cyber-Physical Production Systems Based on **Machine Learning and Residual-Based Diagnosis Models**

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Motivation: Modern Cyber-Physical Production Systems (CPPSs) are getting more and more modular to deal with shorter product life-cycles. But the modularity increases the complexity and traditional diagnosis approaches, such as heuristic methods, are no longer suitable. For model-based approaches it is hard to create and maintain the systems' model, especially, if it is a regular changing system. Additionally, modern CPPSs are typically hybrid, so they contain discrete and continuous signals, and they might be large, so the diagnosis runtime is an important aspect. **Objectives:** We propose a novel residual-based diagnosis algorithm (RDA) that tackles the challenges of hybrid, modular, and large CPPSs. A data-driven approach is used to create the system descriptions with low manual effort to allow for regular changes of the CPPSs.



s⁺(v{ູາ})

 $v_k = 1 \wedge v_{h_1} = 0 \wedge v_{h_2} = 0$

s⁻(v_ϑ)

 $e_{v,g}^{m_1}$

 $v_{m} = 1 \land v_{h_{1}} = 1 \land v_{h_{2}} = 1$

M2

s+(v_d)

 $e_{vd}^{m_2}$

Idea Training Phase: Learn automaton from discrete variables, Mode M; which separates the Measurebehavior into modes ments Hybrid Production Learn model of values Observations System from continuous variables over time in each mode Compute Qualitative Residuals Create system description that Mode M_i shows the relation between

Components heath state, mode and residual

Operating Phase:

Automaton Contin Model Learned Models System Description Diagnosis Model for Point in Time t

Model Learning

Learn automaton:

 $e_{vd}^{m_0}$ The automaton separates the systems' behavior into different modes. Every mode is a unique $v_k = 0 \land v_m = 0$ representation of discrete variables. This enables to deal with state-based systems, but requires the system to be synchronized.

Learn continuous model:

The model represents the value of continuous variables over time. We use a machine learning approach based on neural networks that predicts the expected values given the time since the beginning of each mode.

 $s^+(v_d)$

s⁻(v_d)

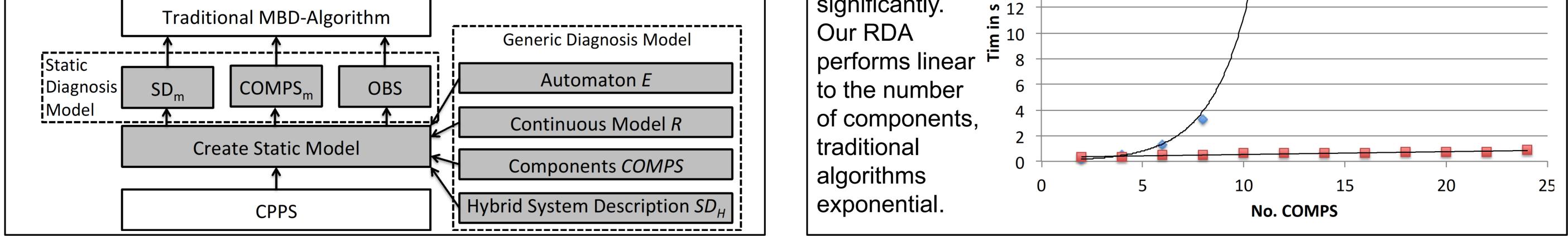
- Compute residuals
- Create static diagnosis model
- Compute diagnosis with traditional algorithms

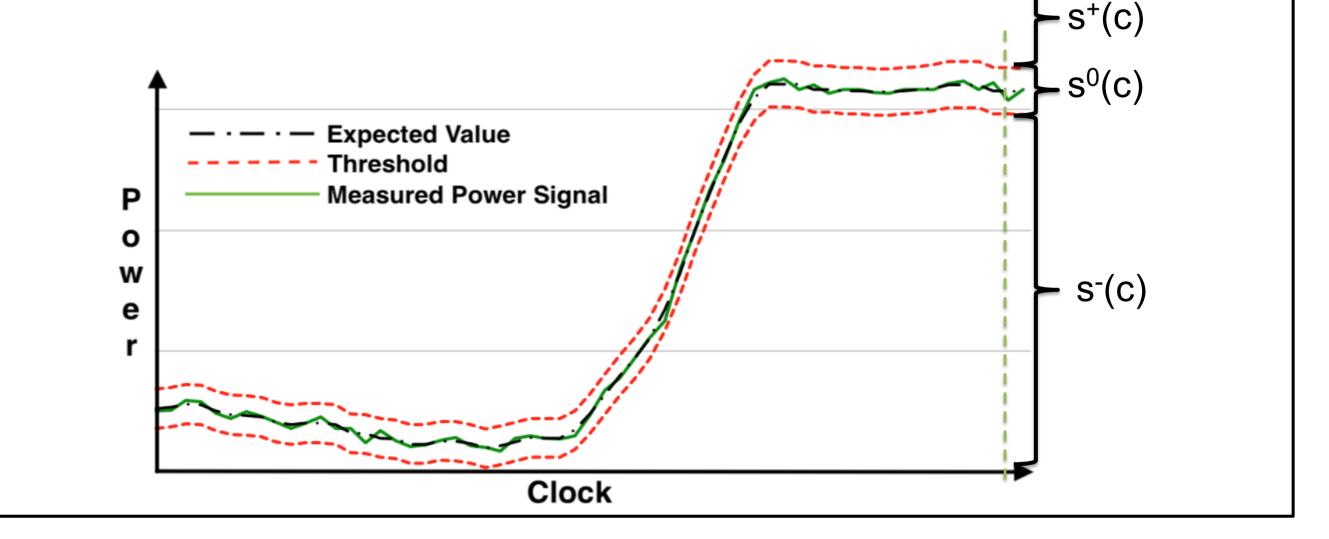
General Approach

Generic Diagnosis Model contains information that enables to diagnose the system at all points in time.

Static Diagnosis Model is a reduced model that is only valid for a single point in time. It is compatible to models from traditional modelbased diagnosis, so high performance algorithms from traditional model-based diagnosis can be used. To create the static model, the following steps are performed:

- Determine the current mode
- Compute the residuals of all continuous variables

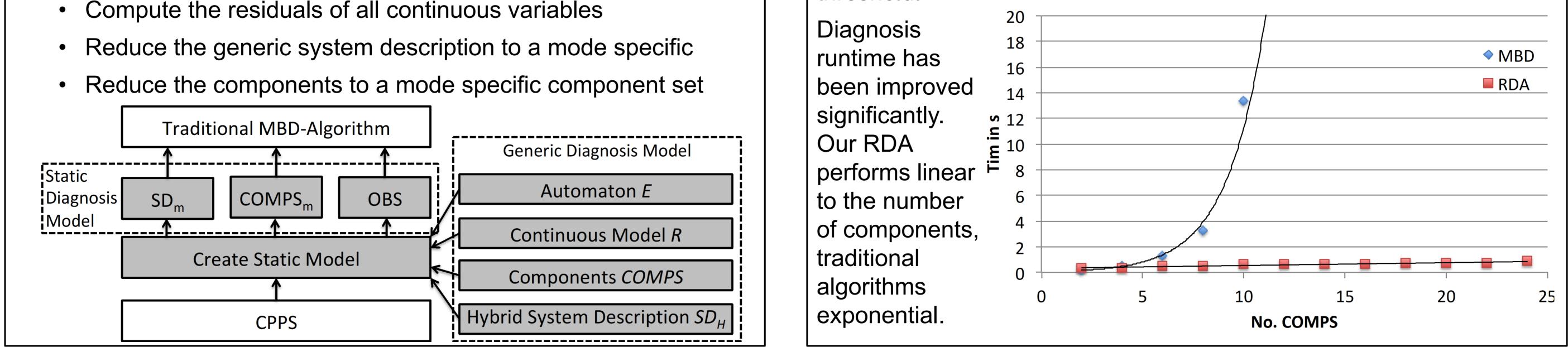




Evaluation

85 % of continuous faults have been diagnosed correctly. If they have not been diagnosed correctly, the residuals were incorrect, which means that there was a bad continuous model or a suboptimal threshold.

Diagnosis runtime has been improved significantly.



Acknowledgments: The work was supported by the German Federal Ministry of Education and Research (BMBF) under the project "KOARCH" (funding code: 13FH007IA6).

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