Application

2015-03-31

2015-04189	Frisk, Erik	NT-14

Information about applicant

Name: Erik Frisk

Doctorial degree: 2001-11-20

Birthdate: 19711130

Academic title: Docent

Gender: Male

Employer: No current employer

Administrating organisation: Linköpings universitet

Project site: Institutionen för systemteknik (ISY)

Information about application

Call name: Forskningsbidrag Stora utlysningen 2015 (Naturvetenskap och teknikvetenskap)

Type of grant: Projektbidrag

Focus: Fri

Subject area:

Project title (english): Diagnostic fault isolation performance of models and algorithms

Project start: 2016-01-01

Project end: 2019-12-31

Review panel applied for: NT-14, NT-2, NT-13

Classification code: 20202. Reglerteknik, 20205. Signalbehandling

Keywords: Fault detection, Fault isolation, Model based diagnosis

Funds applied for

Year:	2016	2017	2018	2019
Amount:	833,620	833,620	833,620	833,620

Descriptive data

Project info

Project title (Swedish)*

Feldiagnosprestanda hos modeller och algoritmer

Project title (English)*

Diagnostic fault isolation performance of models and algorithms

Abstract (English)*

Introduction of fault tolerance in engineering systems have potential for significant increase in availability, reliability, and safety. Also in emerging areas such as autonomous systems, a fault diagnosis component can be crucial for safe operation of an autonomous ground vehicle or unmanned aerial vehicle since there is no human operator that can handle a failure situation, the system must adapt itself.

A key component in a fault tolerant system is a fault diagnosis system that detects and, more importantly for this project, locates the
faulty component, i.e., isolates the fault. A model based diagnosis system detects and isolates faults by careful comparison of
measurements and predictions based on a mathematical model. Performance of a diagnosis system in terms of detection and isolation capabilities is then directly connected to the quality of the model. The core of this project is how to model uncertainty, predict
possible diagnosis performance based on the model, and then to determine performance of diagnosis algorithms. Performance of fault detectors is a well understood subject, in part due to the close relationship with detection in communication, but this is not true for fault isolation performance which is the main topic of this project.

Two novel research directions are proposed in this project. The first concerns analysis of diagnosis models with the objective to predict possible fault isolation performance of a given model. If sharp upper limits on performance can be derived before any actual detector and/or fault isolation design has been made, this provides a theoretical tool for understanding design limits and what uncertainties in the model that are significant. As an example from a pre-study in the important automotive engine application of misfire detection, performance analysis of a torque model with corresponding data revealed that 1 out of 6 cylinders exhibited significantly different behavior than the rest and therefore this one cylinder required specifically adapted solutions. To obtain such information, before any work on detector design has been done, is clearly of great value.

A second research direction is theory and methods to assess fault isolation performance for algorithms in the same framework as for models. Such results would lead to new ways to design fault detectors, set alarm thresholds, and find best locations for sensors, all of
which are essential steps in a diagnosis system design. Fault isolation performance measures are not currently fully understood and there is a need for methods applicable to industrially relevant classes of models. A common practice is to set the alarm threshold for each
detector such that a given false alarm probability is achieved. This can be proven to be sub-optimal in a system wide analysis, and the research will provide a systematic way of optimizing design and tuning of diagnosis algorithms to increase performance compared to established practices.

A successful project will result in methodology for model analysis, placement of sensors, and automatic tuning of key algorithm parameters in a way that could guarantee fault isolation performance and make automatic tuning and optimization possible in an industrial setting.

Popular scientific description (Swedish)*

Diagnos av tekniska system handlar om metoder för att under normal drift detektera om en eller flera komponenter har fallerat och i
sådana fall även peka ut vilken eller vilka av komponenterna som har felat. I säkerhetskritiska system är det lätt att förstå nyttan; i en
kemisk process, flygplan, eller bromssystem i en bil är det förenat med risk för människor och miljö om fel ej diagnostiserats i tid. För
att rätt åtgärd skall kunna vidtas är det också viktigt att veta exakt vilken komponent som är trasig, fel åtgärd på grund av felaktig
diagnostisk information kan få allvarliga följder. Detta är speciellt tydligt i autonoma fordon där det inte finns en operatör som kan rädda situationen utan fordonet måste själv avgöra vilken åtgärd som är rätt att göra. Emissionsrelaterade lagkrav kräver att alla
personbilar som säljs på de stora marknaderna måste detektera alla fel som ger ökade emissioner. Detta sammantaget motiverar varför det är viktigt att detektera och lokalisera eventuella fel som kan uppstå. Fokus i det här projektet ligger på felutpekningen, även
kallad felisolering. Att veta att någon eller några komponenter är trasiga utan att veta vilka är inte önskvärt. Ett felaktigt byte av
komponent kan vara mycket dyrt, exempelvis svårtillgängliga komponenter kan ha långa leveranstider eller kräva lång tid i verkstad
att byta ut vilket ger lägre tillgänglighet.

Tidigare applikationsorienterade projekt har genererat intressanta grundforskningsfrågor och det här projektet studerar modellbaserad diagnos, en klass av metoder som bygger på att man jämför mätningar från processen med prediktioner från en matematisk modell. Skillnader mellan observerat beteende och det från modellen förväntade beteendet ska sedan användas för att härleda fram vilken eller vilka komponenter som är trasiga. En grundläggande fråga är vilken prestanda som kan förväntas och den fundamentala begränsningen i prestanda ges av den modellosäkerhet vi har. En perfekt modell skulle ge perfekt prestanda, men modeller är aldrig perfekta och detta får direkta konsekvenser på hur säkra diagnoser vi kan ställa.

Detektion av fel och prestanda hos detektorer i allmänhet är välstuderade problem. Kärnan i det här projektet är felisolering, som är mindre välstuderat, och hur förväntad och faktisk kvantifierar felisoleringsprestanda hos diagnossystem kan beräknas. Projektet vilar
på två ben där det första siktar mot att utveckla teori och metoder för att enbart utifrån modellen, vilket är en vetenskaplig nyhet, förutspå möjlig felisoleringsprestanda. Detta skulle ge möjligheter att, utan att faktiskt konstruera ett diagnossystem, uppskatta vad som är möjligt. Det andra benet är att, inom samma ramverk som modellanalysen, analysera prestanda hos diagnosalgoritmer vilket ger möjlighet att analysera designval på ett systematiskt sätt. Intressant är att direkt användning av klassiska metoder för generering av felkänsliga signaler, såsom optimal estimering via Kalman Filter, inte är den optimala lösningen för felisoleringsproblemet. Däremot ger sådana etablerade verktyg, använda på ett eftertänksamt sätt, optimal prestanda och att reda ut exakt hur detta bör göras är ett huvudspår i det föreslagna projektet. Det är också en spännande observation att det inte är optimalt att sätta larmnivåerna för alla test för en given falsklarmssannolikhet vilket är den vanligaste ansatsen. Projektet visar att med olika falsklarmssannolikhet för ingående tester signifikant kan öka prestanda hos diagnossystemet. Men detta bara om balanseringen görs på rätt sätt. Metodik och teoretisk grund för detta har potential att effektivisera exempelvis kalibreringsarbete, något som är resurskrävande, i industriella applikationer.

Uppsättningen sensorer som finns tillgängliga har en direkt påverkan på möjlig prestanda och problemet att hitta de bästa sensorpositionerna visar sig täcka många av kärnfrågorna inom felisolering. Även här visar förstudier att optimeringsproblemet som ställs upp har mycket specifika egenskaper som måste utnyttjas på rätt sätt för att globala optimum skall hittas.

Forskningstemat i projektet; kvantitativa analyser av modeller och algoritmer för att bedöma möjlig och faktisk prestanda hos
felisoleringen är vetenskapligt nytt och ger potential för industriella framsteg i en rad olika typer av industriella applikationer som alla idag använder sig av modellbaserad diagnos.

Project period

Number of project years*

4

Calculated project time*

2016-01-01 - 2019-12-31

Classifications

Select a minimum of one and a maximum of three SCB-codes in order of priority.

Select the SCB-code in three levels and then click the lower plus-button to save your selection.

SCB-codes*	2. Teknik > 202. Elektroteknik och elektronik > 20202. Reglerteknik 2. Teknik > 202. Elektroteknik och elektronik > 20205. Signalbehandling

---

Enter a minimum of three, and up to five, short keywords that describe your project.

Keyword 1*

Fault detection

Keyword 2*

Fault isolation

Keyword 3*

Model based diagnosis

Keyword 4

Keyword 5

Ethical considerations

Specify any ethical issues that the project (or equivalent) raises, and describe how they will be addressed in your research. Also indicate the specific considerations that might be relevant to your application.

Reporting of ethical considerations*

Inga etiska överväganden.

The project includes handling of personal data

No

The project includes animal experiments

No

Account of experiments on humans

No

Research plan

1 Diagnostic fault isolation performance of models and algorithms

1.1 Purpose and aims

Assessment of performance of diagnosis algorithms is essential in industrial applications like automotive, aerospace and process industry. For example, to pass legislative certification in the automotive industry it is required that the on-board diagnosis (OBD) system meets specified quantified performance criteria [1] to be allowed to sell the product. Fault isolation performance, a key component in a diagnosis algorithm, is the main topic of this research project. It is well studied how to ensure certain *detection* performance, but the same understanding for fault isolation performance is not available and it is an open question how to both quantify performance and how to ensure that faulty components are found with a specified significance.

The overall purpose of this project is twofold, first to develop theory and methodology to determine fault diagnosis performance based on a *model only*. This means that, without any fault detection of isolation algorithmic algorithm design/implementation, to be able to evaluate what performance that is possible to achieve. Second goal is to study performance of diagnosis algorithms, in the same framework as models, and analyze the effects on, e.g., threshold selection, observer feedback gain, fault detector design, and selection of sensor locations. Initial experiments in all these areas indicate that interesting results can be obtained already for the most basic problem formulations and this project aims to continue that progress. For example, it is shown why a direct application of the Kalman Filter is not optimal, it is also shown why the optimal sensor placement problem is difficult and what part need to be better understood to be able to obtain efficient algorithms that guarantee finding optimal solutions. Another important topic is threshold selection, i.e., decide when to raise an alarm. A standard way of selecting thresholds is to determine a false alarm probability for each alarm signal and then set the alarm threshold accordingly. However, this is suboptimal for the overall fault isolation performance and there is performance to be gained by introduce a more clever balance among the detectors. In a situation with hundreds of detectors, not an uncommon situation, there is need of methodology and algorithms to support threshold setting.

The outline of the application is, first an overview of the research program followed by a detailed project description that also includes preliminary results and some initial experiments. The application then continues with a field survey, and description of industrial and academic significance.

Overview of research objectives

Diagnosis and supervision typically means to detect if there are any faults acting upon a system and *also* to locate the faulty component, here referred to as fault isolation. This project considers *model based* diagnosis algorithms, an important class of algorithms that is based on a mathematical/formal model of the process where detection and isolation of faults are done by checking consistency between the model and the measurements obtained from sensor readings. This is an approach typically used in cases where the number of sensors are relatively low and the model is the key enabler to do efficient fault diagnosis.

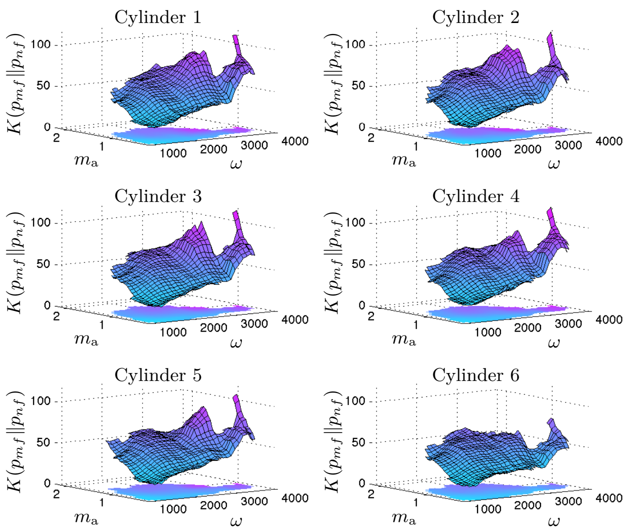


Figure 1: Misfire detection performance for the 6 cylinders in different operating points. The higher the value the easier is the misfire detection problem.

Fault *detection* performance is well studied, in part due to the close relationship with detection in communication applications and there are standard books treating basic material, e.g., [15] and [4]. One defining difference between the detection problem in communication and fault isolation in diagnosis is that fault sizes are unknown, with unknown characteristics, and typically varying in time, while in communication, signal patterns are typically predefined. This is a main reason that fault isolation performance is a less studied topic and more research is needed.

The purpose of this project is to develop theory and methodology to determine diagnostic performance with respect to fault detection, and more importantly fault isolation, of both models and algorithms. To illustrate the project purpose with a motivating example, consider Figure 1 where detection performance for a combustion engine misfire problem is evaluated for 6 cylinders in different operating regions. The performance analysis was based on data and a torque model and directly identifies, without any detector design, problematic operating regions and that cylinder 6 exhibits significantly different behavior than the rest of the cylinders. Further, consider the important topic of sensor placement, i.e., where to put sensors to make diagnosis possible. In the well-cited paper [16], a method was developed that found sets of sensors that fulfilled binary requirements, i.e., specifications of which faults faults that should be able to isolate from each other. These solutions state nothing about performance for the computed sensor sets and a natural extension is to include quantified performance in the sensor placement problem. To approach this extension and to analyze how much performance is gained by adding additional sensors, a first work [11] studied an application where a quantitative measures were introduced. A user then had a tool to continuously verify the performance obtained by the sensor set solutions.

Success in research will result in methods to assess possible performance on a model level, which means that initial indications of final performance can be obtained before any actual diagnosis system design. Further, the project will advance algorithmic development in important topics such as threshold selection, residual generator design, and sensor location for diagnosis.

1.2 Project description

The overall theme of the project is to explore diagnosis performance, in particular fault isolation performance, of *models* and *diagnostic algorithms*. The distinction between model and algorithm performance is at the heart of the project. A main research objective is to quantify performance for both in the same framework such that absolute level of performance, and not only a measure used for optimization, can be computed.

Diagnostic performance of models

It is an attractive notion that diagnostic performance can be evaluated based on a model of the process only, and before any detection or fault isolation algorithms have been designed or implemented. In this way important investigations can be performed before significant design efforts, possibly with significant costs in time and money. It is clear that possible diagnostic performance is closely linked to the uncertainty of the model, with perfect models ideal performance would be possible. Thus some notions of uncertainty need to be introduced in the model.

One way to approach this problem is to model uncertainties using random variables and stochastic processes. This means that all observations from the process also can be described as stochastic processes. Let's consider a very simple time-invariant case where all stochastic process are stationary. Let there be n different fault modes $F_1, \ldots, F_n$ and define sets of possible probability density functions for observations in each fault mode as

$$\mathcal{Z}_i = \{p(\text{observations from fault mode } F_i)\}, \quad i = 1, \ldots, n$$

In this simple problem setup, each element in the sets $\mathcal{Z}_i$ corresponds to the probability distribution of the observations given a specific fault size θ in fault mode F_i. Denote the probability density function for fault mode F_i of with fault size θ with p^i_θ, then for all fault sizes

$$p^i_\theta \in \mathcal{Z}_i$$

With this definition, it is straightforward to define fault isolability. A fault mode F_i is isolable from fault mode F_j if there exists a fault size such that the observations can not come from fault mode F_j. Using the formal objects introduced above, this translates into

$$F_i \text{ isolable from } F_j \Leftrightarrow \mathcal{Z}_i \not\subseteq \mathcal{Z}_j$$

However, this only provides a yes or no answer, very much like for example observability analysis gives a yes or no answer if a mode is observable or note. It does not indicate expected performance of the state estimator. Thus, a main objective is to define a quantitative measure that states not only if it is possible to isolate two faults, but also *how* difficult. To illustrate one property of fault isolation performance, consider Figure 2 where

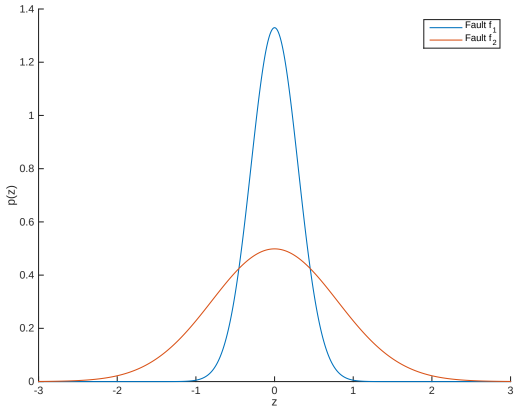


Figure 2: Illustration of the asymmetric property of the fault isolation performance.

the probability density function for an observation z is plotted for two fault modes, fault f_1 and fault f_2. It is easier to isolate f_2 from f_1 since there is a relatively high probability of observations which are likely given f_2 but not f_1. However, observations that are likely given f_1 are also likely given f_2 meaning that even if f_1 is the present fault the residual output could still be explained by the fault f_2. This type of asymmetry must be captured in a isolability performance measure.

One candidate, from [10], is to explore the Kullback-Leibler divergence

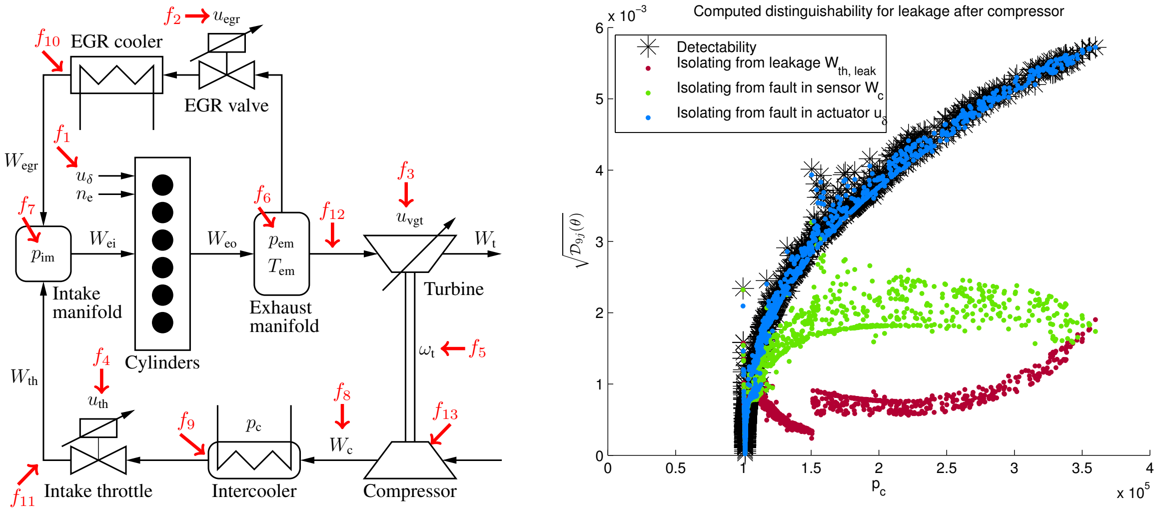
$$K(p^i|p^j) = E_{p^i}\left[\log\frac{p^i}{p^j}\right] = \int_{-\infty}^{\infty}\log\frac{p^i(v)}{p^j(v)}p_i(v)\,dv$$

With this measure, the difficulty of isolating a particular fault size θ for fault mode F_i from fault mode F_j can then be defined as the minimum distance for the observation distribution p^i_θ from any distribution in the set $\mathcal{Z}_j$. Formally, this translates into

$$D_{i,j}(\theta) = \min_{p^j\in\mathcal{Z}_j} K(p^i_\theta, p^j) \tag{1}$$

Thus, $D_{i,j}(\theta)$ measures the ability to isolate a fault F_i of size θ from fault mode F_j. The higher value, the easier is the fault isolation problem. Note that this, by construction is an asymmetric measure. This is in part due to the asymmetry of the Kullback-Leibler divergence, but more importantly due to the minimization formulation. This asymmetry is a natural property of the fault isolation problem as discussed above.

Methods for computing this measure for general systems is an open problem, but it turns out that analysis for even as simple systems as static and Gaussian systems give interesting results. For such systems, it is possible to compute (1) explicitly. One key observation here is that measure (1) has a *direct* connection to the performance of optimal residual generators in the sense that $\sqrt{D_{i,j}(\theta)}$ is the fault to noise ratio of an optimal linear fault detector that isolates fault mode F_i from fault mode F_j. This connection between diagnostic performance of the *model* to performance of diagnosis algorithms is of central importance. To illustrate, consider an automotive engine as schematically showed in Figure 3-a where also a set of relevant faults locations are indicated by arrows. The faults represent, for example, faults in sensors, actuators and leakages. An interesting property of this system is that due to the turbine-compressor linkage and the exhaust gas re-circulation system, feedback is present at all levels in the system. This makes all components in the system interconnected and a fault somewhere will affect all parts of the system. This makes fault isolation non-trivial and scientifically interesting in addition to the immediate industrial relevance. Possible questions to answer could now be: 1) how difficult is it to detect a leakage after the compressor (f_8), 2) how difficult is it to isolate the fault (f_8) from closely related faults such as sensor faults in the air intake sensor (f_{13}) or leakage in the throttle (f_4), 3) how difficult is it to isolate from a fault in the fuel injection (f_1). Even though the engine is a dynamic and non-linear system, static analysis in stationary operating points reveals interesting results summarized in Figure 3-b. Since the system is non-linear, the answer is given as a function of the operating point that in this case corresponds to the pressure after the compressor. The figure shows that isolating fault f_1 from the leakage is about as easy as detecting just detecting the leakage and the figure also shows how detection performance depends on the pressure. It shows the natural relation that detection becomes easier with higher pressures. The figure also shows, in quantitative numbers, how how difficult it is to isolate faults f_4



(a) (b)

Figure 3: Overview of diesel engine model and a plot of fault detection and isolation performance.

and f_{13} from the leakage. Such answers to non-trivial questions are of great importance, especially since they can be obtained using only the model. Thus, analysis of static linear systems is a good first step but it is well known that analysis of dynamic behavior can reveal a lot of fault isolation information and this is an important expected scientific outcome of the project.

A natural next step is to extend the analysis to also dynamic systems, still keeping the linearity assumption. This becomes especially interesting in combination with analysis of operational cycles. For example, in the automotive industry specific driving cycles are used in certification and development. Then, research questions are, e.g., to compare available fault isolation information in different cycles and to determine in which parts of the cycle that contains fault isolation information. This industrially highly relevant question firs well into the scientific program of the project. For dynamic systems, there is also the fundamental question on how large time-window should be considered. In [11] it was found that, in a special case, asymptotic behavior of the performance could be described by the *static* behavior of a dynamic model. Figure 4 shows the asymptotic behavior for the detection performance, and it is clear that for above $\approx$ 10-12 sample time-window, the linear approximation which can be computed easily, accurately describes the behavior for $N > 12$. Further investigations into this topic will provide tools and results to help design fault isolating residual generators for dynamic systems.

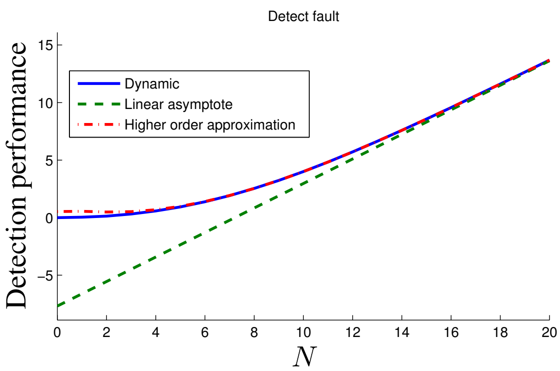


Figure 4: Asymptotic behavior of detectability.

Non-linear and dynamic phenomena is an important extension and a first extension is control-affine systems in the form

$$\dot{x} = g_0(x) + g_u(x)u + g_f(x)f$$
$$y = h_0(x) + h_f(x)f$$

Then tools, like the ones used in [9, 12] can be directly applicable. But when approaching more general model formulations one can not expect explicit expressions and computational tools. For the important case where faults can be represented by changes in parameters, sensitivity analysis is an interesting approach. Consider the system

$$\dot{x} = g(x, f), \quad y = h(x)$$

Let g_x and g_f represent the partial derivative of g with respect to x and f, and let $P(t) = \frac{d}{df}\,x(t)$. Then the standard, linear and time-varying, sensitivity equation,

$$\dot{P} = g_x P + g_f$$

gives an explicit equation for computing $P(t)$ which gives key information in determining fault detectability performance. Even though $P(t)$ alone is not enough, it is still a promising tool to evaluate fault isolation performance for a general class of systems. If this research is successful, this implies that diagnosability analysis could be performed automatically for a large class of models.

Diagnostic performance of algorithms

Above, diagnostic performance was based on only the model equations. To have the same type of measure for a specific diagnostic algorithm would allow us to compare how far from the theoretical limit the particular design is. Simply speaking, as long as

$$\mathcal{D}^{\text{algorithm}} \ll \mathcal{D}^{\text{model}}$$

there are still algorithmic improvements to be made. For this to be possible, it is required that algorithms can be evaluated in the same framework as models and that the performance quantity has a fundamental connection to detection performance in the sense of probability of false alarms, probability of detection, or probability of correctly isolating a fault. In [10] it was shown how algorithmic performance could be evaluated in the same framework as models for static Gaussian models.

A main expected contribution of the project is the development and analysis of overall performance criteria, something that is not covered in existing literature. Let $\mathcal{D}^{\mathcal{M}}$ be the true set of diagnoses, the ones we aspire to find, in a given situation and $\mathcal{D}^{\text{alg}}$ the diagnoses computed by an algorithm. Then, one possible definition of overall performance could be formalized using

$$P(\text{correct diagnosis}) = P(\mathcal{D}^{\text{alg}} = \mathcal{D}^{\mathcal{M}}) = \sum_{FM \in \mathcal{F}} P(\mathcal{D}^{\text{alg}} = \mathcal{D}^{\mathcal{M}} | FM) P(FM) \quad (2)$$

where $\mathcal{F}$ is the set of failure modes. However, this is not necessarily a good formulation and an alternative of a correct diagnosis is that the present fault mode f_p is one of the explanations computed by the diagnostic algorithms. In particular this becomes interesting when the diagnostic algorithm computes $\mathcal{D}^{\text{min}}$, the set of minimal diagnoses, which is the set of (subset) simplest explanations for the observed behavior [19]. Formally, this translates into

$$P(\text{correct diagnosis}) = P(f_p \in \mathcal{D}^{\text{min}}) = \sum_{FM} P(f_p \in \mathcal{D}^{\text{min}} | FM) P(FM) \quad (3)$$

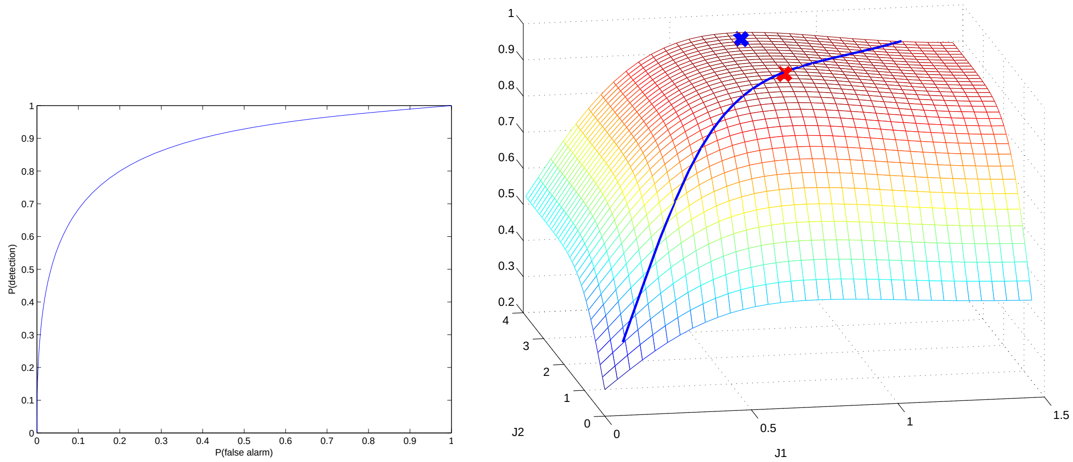
These are two examples of overall performance specifications for a complete diagnosis system. Both are reasonable but they have distinctly different characteristics and thus significantly affects algorithm tuning.

Given a quantity to evaluate diagnostic performance on a system level such as (2) or (3) allows for systematic studies of parameter tuning of specific algorithms, algorithm selection, and overall system performance. By overall system performance is meant the possibility to evaluate the decision-making process, based on the output of the diagnosis algorithm. For example, in a fault tolerant controller, different control strategies are used depending on the current fault situation and with the performance measure, the effectiveness of the fault tolerant control system on a system level can be evaluated, for example as in [2].

With quantified performance measures, there are important design choices when designing diagnosis systems that can be studied systematically. Examples of three fundamental research directions that will be pursued in the project are: 1) threshold selection, 2) residual generator design, and 3) sensor placement which will be discussed further below.

Threshold selection

Setting alarm thresholds is a key design choice when designing a diagnosis system. All designs that are based on a set of alarms from fault detectors need to set a limit when to raise the alarm and this covers almost all proposed detection algorithms. The basic trade-off when setting thresholds is to balance the probability of false alarms against the probability of missed detection, commonly illustrated using ROC-curves as in Figure 5-a. The algorithm designer can position the detector anywhere on the curve using the choice of alarm threshold.



(a) (b)

Figure 5: Typical ROC-curve and overall diagnosis performance as a function of two thresholds in a small example.

This balance has traditionally been seen as a user choice and the most common approach is to set a suitable false alarm probability, set the threshold accordingly and validate the detection performance. Such an approach is then done on individual test case basis, meaning that the interaction and dependencies between the residuals/detectors are not taken into account. This indicates that the simple false alarm approach might lead to an overall sub-optimal design.

A more systematic approach would be to base the design on an overall objective function, for example (2) or (3) and optimize the set of thresholds as

$$J^* = \arg\min_J P(\text{corr. diagnosis}; J)$$

It straightforward to connect and extend the performance directly to decision making and risk analysis of functions rather than diagnostic performance [2]. This could be applied to direct thresholding, but also more involved evaluation techniques such as [20].

To illustrate, consider a small academic example with two residuals that are designed to detect and isolate two faults. The residuals are sensitive to the faults, and are each subjected to Gaussian noise with different standard deviations. Figure 5-b shows the overall performance, according to (3), as a function of thresholds J_1 and J_2. The blue cross indicates the global optimum, the blue line the performance obtained by setting the false alarm equal in the two residuals, and finally the red cross corresponds to the optimal performance with the same false alarm probability. In this example it is clear that significant performance gain can be obtained by a proper balance of false alarm probability in the two tests. In this small example, detection performance in residual 1 is prioritized, due to a smaller threshold J_1, compared to residual 2 and this resulted in an overall performance increase.

For simplicity of this example, the noise processes in each residual are assumed independent. However, in connected systems like the automotive engine discussed earlier, the same sensors and the same model are used in the different residuals. This means that it is inherent in the problem with correlated disturbances in the residuals, i.e., if one residual raises an alarm due to disturbances, the probability of the other residuals raising a false-alarm then also increases. Taking this into account is suspected to further introduce skewness in the optimal choice of false alarm rate for the different residuals.

Thus, this will be a main research direction; analyze and find methods for choosing thresholds, especially for cases when there are many, possibly hundreds, of stochastic and dependent residuals.

Residual generator design

Performance also has interesting implications on residual generator design. To illustrate this, consider the simple case of triple sensor redundancy where three sensors measures the same quantity x and the objective is to detect a fault in the third sensor:

$$\begin{aligned} y_1 &= x + \varepsilon_1, & \varepsilon_1 &\sim \mathcal{N}(0,2) \\ y_2 &= x + \varepsilon_2, & \varepsilon_2 &\sim \mathcal{N}(0,1) \\ y_3 &= x + \varepsilon_3 + f, & \varepsilon_3 &\sim \mathcal{N}(0,0.5) \end{aligned}$$

Let $\hat{x}_{mv}(y_1, y_2, y_3)$ denote the minimum variance estimate of x using all three sensors, then one straightforward way of detecting the fault would be to compute the residual

$$r_1 = y_3 - \hat{x}_{mv}(y_1, y_2, y_3)$$

This is an often used approach; to detect a sensor fault, design a Kalman Filter and compare the estimated output with the measured. However, in this simple triple redundancy case it is straightforward to show that this is not an optimal design, but rather the detector

$$r_2 = y_3 - \hat{x}_{mv}(y_1, y_2)$$

The take home message from this small example is that the standard approach

$$\begin{aligned} x_{t+1} &= g(x_t, u_t, f_t) + v_t \\ y_t &= h(x_t, u_t, f_t) + \varepsilon_t \end{aligned}$$

$$r = y_t - \hat{y}_t$$

where $\hat{y}_t$ is estimated using, for example a Kalman Filter, and then compare to the measured output is not an optimal design. There is a simple extension of the triple redundancy case to sensor faults with more than one sensor. Then the best choice is to estimate the monitored output, using all sensors *except* the one we are monitoring, and then compare with the monitored output.

Processes are not only affected by sensor faults and the corresponding extension for faults that affect the dynamic equations is non-trivial. Without loss of generality, one can assume that the process fault affect one dynamic equation directly. Consider the non-linear descriptor system

$$\begin{aligned} x^1_{t+1} &= g_1(x^1_t, x^2_t, u_t, f_t) + v^1_t \\ x^2_{t+1} &= g_2(x_t, x^2_t, u_t) + v^2_t \\ y_t &= h(x_t, x^2_t, u_t, f_t) + \varepsilon_t \end{aligned}$$

with two state variables where x^1_t is the state directly influenced by the fault f_t and x^2_t all other states. Then, a similar approach for the model would be to estimate y_t as good as possible in

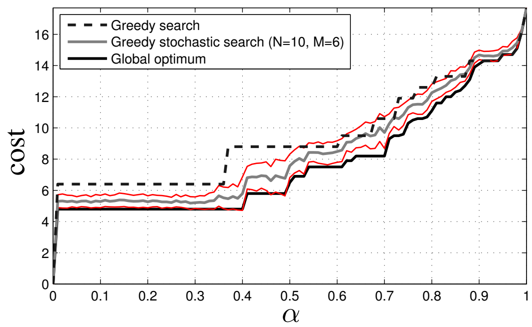
$$\begin{aligned} x^2_{t+1} &= g_2(x_t, x^2_t, u_t) + v^2_t \\ y_t &= h(x_t, x^2_t, u_t, f_t) + \varepsilon_t \end{aligned}$$

to compute the residual. Thus, estimation in descriptor models, for example as in [3], is an important topic for residual generator design.

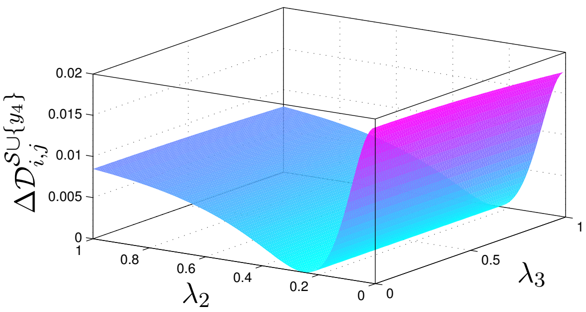
Sensor placement

A third research direction to pursue within the algorithmic track is the sensor placement problem and the role of quantitative performance measures. Locations of the sensors naturally have a significant influence on possible diagnosis performance. The basic problem setup is that a set of sensors $\mathcal{S} \subset \mathcal{O}$ should be selected such that cost is minimized and the obtained performance $\mathcal{D}^{\mathcal{S}}_{i,j}$ fulfill the requirements $\mathcal{D}^{req}_{i,j}$, i.e., similar to

$$\begin{aligned} \min_{\mathcal{S} \subseteq \mathcal{O}} \quad & \sum_{y_l \in \mathcal{S}} \text{cost}(y_l) \\ s.t. \quad & \mathcal{D}^{\mathcal{S}}_{i,j} \geq \mathcal{D}^{\text{req}}_{i,j}, \forall i, j. \end{aligned} \tag{4}$$



(a) Plot of cost of solution as a function of percent α of maximum performance given by using all available sensors.



(b) Performance gain of relaxed problem. The relaxed problem still might have several optima.

Figure 6: Properties of a sensor placement optimization problem.

If the requirements are binary, i.e., only if faults should be isolable or not, then there are published works [18, 7, 16, 14, 13] that could be used to find a solution. Minimum cost solutions with binary constraints typically lead to minimum cardinality solutions if sensor costs are equal or similar.

The solid line in Figure 6-a shows the optimal cost for achieving a specified fraction of maximum performance for a small flow system with 17 possible sensor locations, details of the system is not of importance here but can be found in [11]. Maximum performance corresponds to $\alpha = 1$ which is obtained if all 17 sensors are used. From this plot it is clear that with binary requirements, which corresponds to $\alpha = \epsilon > 0$, the maximum performance is achieved already with 5 sensors. However, according to the plot this only achieves up to 40% of maximum performance, all depending on which 5 sensors that are used. In a case where the performance of the minimal sensor setup is not sufficient, non-binary requirements in (4) are needed such that an absolute level of diagnosis performance can be stated.

The discrete optimization problem (4) is difficult, mainly because the performance gain when adding a sensor is highly dependent on which sensors that have already been considered, i.e., the gain of using a sensor is dependent on all other sensors used. This further means that local approaches, such as greedy searches, will not find the optimum. To illustrate the difficulties, convert the discrete optimization problem into a continuous problem through relaxation by introducing $\lambda_i \in [0, 1]$ where λ_i equal to 1 means full usage of sensor y_i and 0 that the sensor is not used. A typical plot, obtained from the same flow example as discussed above, showing the cost as a function of λ_i is shown in Figure 6-b. From the figure it is clear that the problem has local maxima and, for example, a gradient based optimization approach will not necessarily converge to the optimal solution. this is a typical situation and the objective of the research is how to avoid the exhaustive search with its corresponding exponential complexity.

This part of the research proposal then concerns further understanding of the connection between diagnostic performance and sensor locations. In particular, study of how much performance is gained by adding a sensor y_k to an already used sensor set S, i.e.,

$$\mathcal{D}_{i,j}^{\mathcal{S}\cup\{y_k\}} - \mathcal{D}_{i,j}^{\mathcal{S}} \qquad (5)$$

This quantity is the key to efficient optimal sensor placement. It will be difficult, for the reasons outlined above, to find an explicit expression of (5), but a non-conservative underestimation is sufficient since then AI search approaches, like A*, or other more advanced search methods, can be used to efficiently find the global optimum.

1.3 Survey of the field

Model based diagnosis (MBD) is a maturing field and there are many books available, a book that is often used as a key general reference in the field from a control oriented perspective is [6]. Assessing diagnosability of models directly, without considering a particular design, is a novel area and the main reference here is our previous work [10] which covers static systems and dynamic systems on a time window with Gaussian noise uncertainty descriptions. A number of smaller applications and investigations using the basic results have also been published as conference papers.

The basic detection problem is a mature subject and there are many well established papers and books. Good examples are [15], which treats general detection problems, and [4] from a perspective closer to fault diagnosis. Both works set thresholds on an individual test basis by exploring receiver operating curves and probability for false alarms. This body of work is therefore an excellent resource for fault detection but there is no treatment of the overall fault isolation problem.

A key to study the overall performance of *fault isolation* is to exploit the theoretical foundations for fault isolability that originates from the the AI community where key works are [19, 8]. The AI works uses logic based frameworks and connecting the logic foundations to more control oriented approaches is an active research topic, and is also a key step in this project for analyzing the effects on diagnosis performance by model uncertainty and measurement noise. The work [21] is a recent work that summarizes this connection but again does not treat the model uncertainty and its effects on fault isolation. By introducing overall performance specification, it is possible to simultaneously select thresholds for all test, or possibly the parameters in more advanced approaches such as [20]. Residual generation for DAE models appear naturally in the context of fault isolation. Observers for differential-algebraic models has been studied, for example in the works [5, 17, 23], and also in our own work [3]. These works will be important in the study of observer based residual generators for fault isolation in this project.

Placement of sensors directly relates to the core properties of fault isolation. In published works, fault isolation requirements are binary in the sense that either faults can be isolated or not. Important works in fault isolation are [18], [7], and [22]. The problem was given a more formal treatment, with corresponding efficient methods, for structural models in our work [16] or [13]. The theory was then extended to differential-algebraic models in [14]. All these previous works only treated binary isolation requirements, and a first work to quantify isolation performance in sensor placement is [11] which built on the results in [10].

1.4 Significance

Significance of the research project is outlined in both the project description and in the research field survey. A main original research direction is the idea of model based fault isolation performance evaluation directly on the model equations and/or measured data, not on a particular diagnosis algorithm implementation. In addition, the focus on fault isolation, quantitative performance and the effects on diagnostic algorithm design is novel. To achieve this it is important that algorithms can be evaluated in the same framework as models.

A main contribution of a successful project would be to increase the set of classes of problems/models where it is possible to do model analysis, placement of sensors, and automatic tuning of algorithm parameters such as observer feedback gains and detection thresholds. This is industrially important since, for example in the automotive industry, embedded control systems run hundreds of detection tests. And since optimal overall performance is not obtained by setting each threshold individually, automatic tuning methods has the potential to save significant engineering time and calibration efforts.

1.5 Preliminary results

References and descriptions of preliminary results, both published and non-published, are described in the project description section.

References

[1] California's OBD-II regulation. *section 1968.2, Title 13, California Code of Regulations, July 31*, 2013. URL: http://www.arb.ca.gov/msprog/obdprog/obdregs.htm.

[2] Jan Åslund, Jonas Biteus, Erik Frisk, Mattias Krysander, and Lars Nielsen. Safety analysis of autonomous systems by extended fault tree analysis. *International Journal of Adaptive Control and Signal Processing*, 21(2-3):287–298, 2007.

[3] Jan Åslund and Erik Frisk. An observer for non-linear differential-algebraic systems. *Automatica*, 42(6):959–965, 2006.

[4] Michèle Basseville, Igor V Nikiforov, et al. *Detection of abrupt changes: theory and application*, volume 104. Prentice Hall Englewood Cliffs, 1993.

[5] Victor Manuel Becerra, P.D. Roberts, and G.W. Griffiths. Applying the extended kalman filter to systems described by nonlinear differential-algebraic equations. *Control Engineering Practice*, 9(3):267–281, 2001.

[6] Mogens Blanke, Michael Kinnaert, Jan Lunze, and Marcel Staroswiecki. *Diagnosis and Fault-Tolerant Control*. Springer, 2nd edition, 2006.

[7] C. Commault, J. Dion, and S.Y. Agha. Structural analysis for the sensor location problem in fault detection and isolation. In *Proceedings of IFAC Safeprocess'06*, pages 949–954, Beijing, China, 2006.

[8] Johan de Kleer. Diagnosing multiple faults. *Artificial Intelligence*, 32(1):97–130, 1987.

[9] Claudio De Persis and Alberto Isidori. A geometric approach to nonlinear fault detection and isolation. *IEEE Trans. on Automatic Control*, 46(6):853–865, 2001.

[10] Daniel Eriksson, Erik Frisk, and Mattias Krysander. A method for quantitative fault diagnosability analysis of stochastic linear descriptor models. *Automatica*, 49(6):1591–1600, June 2013.

[11] Daniel Eriksson, Mattias Krysander, and Erik Frisk. Using quantitative diagnosability analysis for optimal sensor placement. Proceedings of IFAC Safe Process 2012, Mexico city, Mexico, 2012.

[12] Erik Frisk and Jan Åslund. Lowering orders of derivatives in non-linear residual generation using realization theory. *Automatica*, 41(10):1799–1807, 2005.

[13] Erik Frisk, Anibal Bregon, Jan Åslund, Mattias Krysander, Belarmino Pulido, and Gautam Biswas. Diagnosability analysis considering causal interpretations for differential constraints. *IEEE Transactions on Systems, Man, and Cybernetics – Part A: Systems and Humans*, 42(5):1216–1229, September 2012.

[14] Erik Frisk, Mattias Krysander, and Jan Åslund. Sensor placement for fault isolation in linear differential-algebraic systems. *Automatica*, 45(2):364–371, 2009.

[15] Steven M Kay. Fundamentals of statistical signal processing: detection theory. 1998.

[16] Mattias Krysander and Erik Frisk. Sensor placement for fault diagnosis. *IEEE Transactions on Systems, Man, and Cybernetics – Part A: Systems and Humans*, 38(6):1398–1410, 2008.

[17] Ramine Nikoukhah, Alan S Willsky, and Bernard C Levy. Kalman filtering and riccati equations for descriptor systems. *Automatic Control, IEEE Transactions on*, 37(9):1325–1342, 1992.

[18] R. Raghuraj, M. Bhushan, and R. Rengaswamy. Locating sensors in complex chemical plants based on fault diagnostic observability criteria. *AIChE*, 45(2):310–322, 1999.

[19] Raymond Reiter. A theory of diagnosis from first principles. *Artificial intelligence*, 32(1):57–95, 1987.

[20] Carl Svärd, Mattias Nyberg, Erik Frisk, and Mattias Krysander. Data-driven and adaptive statistical residual evaluation for fault detection with an automotive application. *Mechanical Systems and Signal Processing*, 45(1):170–192, 2014.

[21] Louise Travé-Massuyès. Bridges between diagnosis theories from control and ai perspectives. In *Intelligent Systems in Technical and Medical Diagnostics*, pages 3–28. Springer, 2014.

[22] Louise Trave-Massuyes, Teresa Escobet, and Xavier Olive. Diagnosability analysis based on component-supported analytical redundancy relations. *IEEE Transactions on Systems, Man, and Cybernetics – Part A: Systems and Humans*, 36(6):1146–1160, 2006.

[23] Gerta Zimmer and Jürgen Meier. On observing nonlinear descriptor systems. *Systems & Control Letters*, 32(1):43–48, 1997.

Interdisciplinarity

My application is interdisciplinary

☐

An interdisciplinary research project is defined in this call for proposals as a project that can not be completed without knowledge, methods, terminology, data and researchers from more than one of the Swedish Research Councils subject areas; Medicine and health, Natural and engineering sciences, Humanities and social sciences and Educational sciences. If your research project is interdisciplinary according to this definition, you indicate and explain this here.

Click here for more information

Scientific report

Scientific report/Account for scientific activities of previous project

---

Budget and research resources

Project staff

Describe the staff that will be working in the project and the salary that is applied for in the project budget. Enter the full amount, not in thousands SEK.

Participating researchers that accept an invitation to participate in the application will be displayed automatically under Dedicated time for this project. Note that it will take a few minutes before the information is updated, and that it might be necessary for the project leader to close and reopen the form.

Dedicated time for this project

	Role in the project	Name	Percent of full time
1	Applicant	Erik Frisk	20
2	Participating researcher	Doktorand	80

Salaries including social fees

	Role in the project	Name	Percent of salary	2016	2017	2018	2019	Total
1	Applicant	Erik Frisk	20	212,520	212,520	212,520	212,520	850,080
2	Participating researcher	Doktorand	80	405,100	405,100	405,100	405,100	1,620,400
	Total			617,620	617,620	617,620	617,620	2,470,480

Other costs

Describe the other project costs for which you apply from the Swedish Research Council. Enter the full amount, not in thousands SEK.

Premises

Type of premises	2016	2017	2018	2019

Running Costs

Running Cost	Description	2016	2017	2018	2019

Depreciation costs

Depreciation cost	Description	2016	2017	2018	2019

Total project cost

Below you can see a summary of the costs in your budget, which are the costs that you apply for from the Swedish Research Council. Indirect costs are entered separately into the table.

Under Other costs you can enter which costs, aside from the ones you apply for from the Swedish Research Council, that the project includes. Add the full amounts, not in thousands of SEK.

The subtotal plus indirect costs are the total per year that you apply for.

Total budget

Specified costs	2016	2017	2018	2019	Total, applied	Other costs	Total cost
Salaries including social fees	617,620	617,620	617,620	617,620	2,470,480		2,470,480
Running costs					0		0
Depreciation costs					0		0
Premises					0		0
Subtotal	617,620	617,620	617,620	617,620	2,470,480	0	2,470,480
Indirect costs	216,000	216,000	216,000	216,000	864,000		864,000
Total project cost	833,620	833,620	833,620	833,620	3,334,480	0	3,334,480

Explanation of the proposed budget

Briefly justify each proposed cost in the stated budget.

Explanation of the proposed budget*

Budgeten omfattar lön, inklusive lönekostnadspåslag och overhead, för projektledare och handledare (20%, senior lön) och doktorand (80%).

Grundlön för senior forskare (huvudsökande; docent): 57 500
Grundlön för doktorand: 27 400
LKP: 54%
Påslag för indirekta kostnader: 35%

Other funding

Describe your other project funding for the project period (applied for or granted) aside from that which you apply for from the Swedish Research Council. Write the whole sum, not thousands of SEK.

Other funding for this project

Funder	Applicant/project leader	Type of grant	Reg no or equiv.	2016	2017	2018	2019

CV and publications

CV

Curriculum Vitae

Erik Frisk
Sturegatan 4
SE-582 21 Linköping
Sverige

(home) +46 (0)13-260888
(work) 013-285714
(email) `frisk@isy.liu.se`

Personal Data

Born	November 30, 1971, Stockholm
Nationality	Swedish

1. Higher education degree

1996	Master of Science in "Computer Science and Engineering", branch of studies "Telematics", Linköping University, Sweden (swe. civilingenjör).
1992	Bachelor of Science in Electrical Engineering, Royal Institute of Technology, Stockholm, Sweden (swe. högskoleingenjör).

2. Doctoral degree

2001	PhD in Electrical Engineering (2001-11-20) under the supervision of Professor Lars Nielsen, Linköping University, Sweden. Dissertation title "Residual generation for fault diagnosis".

3. Postdoctoral positions

2002-2003	Post-doc at Université des Sciences et Technologie de Lille, France. Visited the research group *Sûreté de Fonctionnement des Systèmes Dynamiques*, headed by Professor Marcel Staroswiecki.

4. Docent level

2006	Docent (2006-12-14)

5. Present position

2007-	Position as an associate professor (swe. universitetslektor) at the department of Electrical Engineering, Linköping University, Sweden. Position includes 80% research.

6. Previous positions

2001-2007	Assistant professor (swe. forskarassistent) at the department of Electrical Engineering, Linköping University, Sweden.
1996-2001	PhD-student at the department of Electrical Engineering, Linköping University.

8. Supervision

2007-2011	Main supervisor of Erik Höckerdal. Erik Höckerdal defended his PhD thesis on 2011-05-27 with title "Model Error Compensation in ODE and DAE Estimators with Automotive Engine Applications".
2010-	Main supervisor of Daniel (Eriksson) Jung. Daniel Jung defended his lic thesis on April 5, 2013 with title "Diagnosability analysis and FDI system design for uncertain systems". PhD planned May 22, 2015.
2015-	Main supervisor of PhD student Sergii Voronov.
2015-	Main supervisor of PhD student Fatemeh Mohseni.
2014-2014	Main supervisor of Patrik Önnegren (ended his PhD position after 7 months).
2013-	Main supervisor of post. doc Chih-Feng Lee.
2014-	Main supervisor of post. doc Kok Yew Ng.
2008-	Co-supervisor of PhD student Peter Nyberg, PhD planned June 10, 2015.
2007, 2012, 2014	Co-supervisor of PhD students (PhD year): Carl Svärd (2012), Jonas Bitéus(2007), Emil Larsson (2014), and Christofer Sundström (2014).

9. Other merits

	Research funding
IRIS	Main university applicant in Vinnova/FFI project "Integrerat dynamiskt prognostiserande underhållsstöd" together with Scania. 4 year project.
Volvo	Obtained funding from Volvo Cars for two industrial projects, Misfire detection (2013, Daniel Jung) and Automotive fault isolation (Kok Yew Ng, 2014-2015)
Faculty funds	Financing from the faculty for "Future research leaders" (swe. karriärskontrakt).
TurboPower	Main applicant of the three year research project "Diagnosis and Supervision of Industrial Gas Turbines" funded by Energimyndigheten.
VR	2006 and 2010 granted "projektbidrag" for three year projects.
NFFP4	Main university applicant for Vinnova project "Prognostics for aircraft systems".
	International Collaborations
Invited speaker	Short course in diagnosis during summer 2009 and 2010 at the Automatic Control group, Universitat Politecnica de Catalunya, Spain.
DX'2009	Principal organizer of the 20:th International Workshop on Principles of Diagnosis, Stockholm, June 2009. *http://www.isy.liu.se/dx09/*
IPC	IPC member of major diagnosis related international conferences in the automtic control and AI community; ACD2010, DX'2010, DX'2011, DX'2013, DX'2014, Safeprocess'2012, Safeprocess'2015, SysTol'10, and SysTol'13.
Symposium tutorial	Invited to give symposium tutorial on "Structural methods for analysis and design of large-scale diagnosis systems" at Safeprocess 2015, Paris, France.
Research	Active collaboration with research groups in Lille, France; Universitat Politecnica de Catalunya, Spain; Universitat de Girona, Spain; Vanderbilt University, USA; Università degli Studi di Salerno, Italy.

March 30, 2015

Publication list

List of publications

Source for citation data is google scholar. The five most important publications for this project is marked with ⋆ and the five most cited journal papers are marked with ⋆⋆. Citation statistics is only included for journal papers.

1. Peer-reviewed original articles

[J1] Daniel Jung, Lars Eriksson, Erik Frisk, and Mattias Krysander. Development of misfire detection algorithm using quantitative FDI performance analysis. *Control Engineering Practice*, 34(0):49–60, 2015. Number of citations:.

[J2] Christofer Sundström, Erik Frisk, and Lars Nielsen. A new electric machine model and its relevance for vehicle level diagnosis. *International Journal of Modeling, Identification and Control (IJMIC)*, Accepted for publication. Number of citations:.

[J3] Carl Svärd, Mattias Nyberg, Erik Frisk, and Mattias Krysander. Data-driven and adaptive statistical residual evaluation for fault detection with an automotive application. *Mechanical Systems and Signal Processing*, 45(1):170–192, 2014. Number of citations: 6. ⋆

[J4] Christofer Sundström, Erik Frisk, and Lars Nielsen. Selecting and utilizing sequential residual generators in FDI applied to hybrid vehicles. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 44(2):172–185, February 2014. Number of citations: 2.

[J5] Tomas Nilsson, Christofer Sundström, Peter Nyberg, Erik Frisk, and Mattias Krysander. Robust driving pattern detection and identification with a wheel loader application. *International Journal of Vehicle Systems Modelling and Testing*, 9(1):56–76, 2014. Number of citations: 1.

[J6] Emil Larsson, Jan Åslund, Erik Frisk, and Lars Eriksson. Gas turbine modeling for diagnosis and control. *Journal of Engineering for Gas Turbines and Power*, 136(7):17 pages, July 2014. Number of citations:.

[J7] Carl Svärd, Mattias Nyberg, and Erik Frisk. Realizability constrained selection of residual generators for fault diagnosis with an automotive engine application. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 43(6):1354–1369, 2013. Number of citations:.

[J8] Daniel Eriksson, Erik Frisk, and Mattias Krysander. A method for quantitative fault diagnosability analysis of stochastic linear descriptor models. *Automatica*, 49(6):1591–1600, June 2013. Number of citations: 16. ⋆

[J9] Carl Svärd, Mattias Nyberg, Erik Frisk, and Mattias Krysander. Automotive engine FDI by application of an automated model-based and data-driven design methodology. *Control Engineering Practice*, 21(4):455–472, 2013. Number of citations: 11.

[J10] Erik Frisk, Anibal Bregon, Jan Åslund, Mattias Krysander, Belarmino Pulido, and Gautam Biswas. Diagnosability analysis considering causal interpretations for differential constraints. *IEEE Transactions on Systems, Man, and Cybernetics – Part A: Systems and Humans*, 42(5):1216–1229, September 2012. Number of citations: 15. ⋆

[J11] Albert Rosich, Erik Frisk, Jan Åslund, Ramon Sarrate, and Fatiha Nejjari. Fault diagnosis based on causal computations. *IEEE Transactions on Systems, Man, and Cybernetics – Part A: Systems and Humans*, 42(2):371–381, 2012. Number of citations: 15.

[J12] Jonas Biteus, Erik Frisk, and Mattias Nyberg. Distributed diagnosis using a condensed representation of diagnoses with application to an automotive vehicle. *IEEE Transactions on Systems, Man, and Cybernetics – Part A: Systems and Humans*, 41(6):1262–1267, November 2011. Number of citations: 6.

[J13] Erik Höckerdal, Erik Frisk, and Lars Eriksson. EKF-based adaptation of look-up tables with an air mass-flow sensor application. *Control Engineering Practice*, 19(5):442–453, 2011. Number of citations: 15.

[J14] Mattias Krysander, Fredrik Heintz, Jacob Roll, and Erik Frisk. FlexDx: A reconfigurable diagnosis framework. *Engineering Applications of Artificial Intelligence*, 23(8):1303–1313, October 2010. Number of citations: 5.

[J15] Mattias Krysander and Erik Frisk. Leakage detection in a fuel evaporative system. *Control Engineering Practice*, 17(11):1273 – 1279, 2009. Number of citations: 6.

[J16] Jonas Biteus, Mattias Nyberg, Erik Frisk, and Jan Åslund. Determining the fault status of a component and its readiness, with a distributed automotive application. *Engineering Applications of Artificial Intelligence*, 22(3):363–373, 2009. Number of citations: 3.

[J17] Ylva Nilsson, Erik Frisk, and Lars Nielsen. Weak knock characterisation and detection for knock control. *Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering*, 223(1):107–129, 2009. Number of citations:.

[J18] Erik Frisk, Mattias Krysander, and Jan Åslund. Sensor placement for fault isolation in linear differential-algebraic systems. *Automatica*, 45(2):364–371, 2009. Number of citations: 34. $\star$

[J19] Erik Höckerdal, Erik Frisk, and Lars Eriksson. Observer design and model augmentation for bias compensation with a truck engine application. *Control Engineering Practice*, 17(3):408–417, 2009. Number of citations: 17.

[J20] Erik Höckerdal, Lars Eriksson, and Erik Frisk. Air mass-flow measurement and estimation in diesel engines equipped with EGR and VGT. *SAE International Journal of Passenger Cars - Electronic and Electrical Systems*, 1(1):393–402, 2008. Number of citations: 14.

[J21] Mattias Krysander and Erik Frisk. Sensor placement for fault diagnosis. *IEEE Transactions on Systems, Man, and Cybernetics – Part A: Systems and Humans*, 38(6):1398–1410, 2008. Number of citations: 76. $\star, \star\star$

[J22] Jonas Biteus, Mattias Nyberg, and Erik Frisk. An algorithm for computing the diagnoses with minimal cardinality in a distributed system. *Engineering Applications of Artificial Intelligence*, 21(2):269–276, 2008. Number of citations: 3.

[J23] Jan Åslund, Jonas Biteus, Erik Frisk, Mattias Krysander, and Lars Nielsen. Safety analysis of autonomous systems by extended fault tree analysis. *International Journal of Adaptive Control and Signal Processing*, 21(2-3):287–298, 2007. Number of citations: 12.

[J24] Mattias Nyberg and Erik Frisk. Residual generation for fault diagnosis of systems described by linear differential-algebraic equations. *IEEE Transactions on Automatic Control*, 51(12):1995–2000, 2006. Number of citations: 28.

[J25] Jan Åslund and Erik Frisk. An observer for non-linear differential-algebraic systems. *Automatica*, 42(6):959–965, 2006. Number of citations: 29. $\star\star$

[J26] Erik Frisk and Lars Nielsen. Robust residual generation for diagnosis including a reference $\star\star$

model for residual behavior. *Automatica*, 42(3):437–445, 2006. Number of citations: 76.

[J27] Dilek Dustegör, Erik Frisk, Vincent Coquempot, Mattias Krysander, and Marcel Staroswiecki. Structural analysis of fault isolability in the DAMADICS benchmark. *Control Engineering Practice*, 14(6):597–608, 2006. Number of citations: 56. ⋆⋆

[J28] Erik Frisk and Jan Åslund. Lowering orders of derivatives in non-linear residual generation using realization theory. *Automatica*, 41(10):1799–1807, 2005. Number of citations: 14.

[J29] Dilek Dustegor, Vincent Coquempot, Marcel Staroswiecki, and Erik Frisk. Isolabilité structurelle des défaillances - application à un modèle de vanne. *Journal européen des systèmes automatisés*, 38(1-2):103–124, 2004. Number of citations:.

[J30] Erik Frisk and Mattias Nyberg. A minimal polynomial basis solution to residual generation for fault diagnosis in linear systems. *Automatica*, 37(9):1417–1424, September 2001. Number of citations: 64. ⋆⋆

2. Peer-reviewed conference contributions

[C1] Christofer Sundström, Erik Frisk, and Lars Nielsen. Fault monitoring of the electric machine in a hybrid vehicle. In *7th IFAC Symposium on Advances in Automotive Control*, Tokyo, Japan, 2013.

[C2] Daniel Eriksson, Lars Eriksson, Erik Frisk, and Mattias Krysander. Flywheel angular velocity model for misfire and driveline disturbance simulation. In *7th IFAC Symposium on Advances in Automotive Control*, Tokyo, Japan, 2013.

[C3] Peter Nyberg, Erik Frisk, and Lars Nielsen. Driving cycle adaption and design based on mean tractive force. In *7th IFAC Symposium on Advances in Automotive Control*, Tokyo, Japan, 2013.

[C4] Emil Larsson, Jan Åslund, Erik Frisk, and Lars Eriksson. Fault tolerant supervision of an industrial gas turbine. In *ASME Turbo Expo 2013-GT2013*, San Antonio, USA, 2013. ASME.

[C5] Daniel Eriksson, Erik Frisk, and Mattias Krysander. A sequential test selection algorithm for fault isolation. In *10th European Workshop on Advanced Control and Diagnosis*, Copenhagen, Denmark, 2012.

[C6] E. Noack, A. Luedtke, I. Schmitt, T. Noack, E. Schaumlöffel, E. Hauke, J. Stamminger, and E. Frisk. The columbus module as a technology demonstrator for innovative failure management. Deutcher Luft- und Raumfahrtkongress, Berlin, Germany, 2012.

[C7] Daniel Eriksson, Mattias Krysander, and Erik Frisk. Using quantitative diagnosability analysis for optimal sensor placement. Proceedings of IFAC Safe Process 2012, Mexico city, Mexico, 2012.

[C8] Erik Höckerdal, Erik Frisk, and Lars Eriksson. Bias reduction in DAE estimators by model augmentation: Observability analysis and experimental evaluation. In *50th IEEE Conference on Decision and Control*, Orlando, Florida, USA, 2011.

[C9] Daniel Eriksson, Mattias Krysander, and Erik Frisk. Quantitative stochastic fault diagnosability analysis. In *50th IEEE Conference on Decision and Control*, Orlando, Florida, USA, 2011.

[C10] Carl Svärd, Mattias Nyberg, Erik Frisk, and Mattias Krysander. A data-driven and probabilistic approach to residual evaluation for fault diagnosis. In *50th IEEE Conference on Decision and Control*, Orlando, Florida, USA, 2011.

[C11] Christofer Sundström, Erik Frisk, and Lars Nielsen. Residual generator selection for fault diagnosis of hybrid vehicle powertrains. In *IFAC World Congress*, Milano, Italy, 2011.

[C12] Jan Åslund, Anibal Bregon, Mattias Krysander, Erik Frisk, Belarmino Pulido, and Gautam Biswas. Structural diagnosability analysis of dynamic models. In *IFAC World Congress*, Milano, Italy, 2011.

[C13] Emil Larsson, Jan Åslund, Erik Frisk, and Lars Eriksson. Health monitoring in an industrial gas turbine application by using model based diagnosis techniques. In *ASME Turbo Expo 2011-GT2011*, Vancouver, Canada, 2011. ASME.

[C14] Daniel Eriksson, Mattias Krysander, and Erik Frisk. Quantitative fault diagnosability performance of linear dynamic descriptor models. 22nd International Workshop on Principles of Diagnosis (DX-11), Murnau, Germany, 2011.

[C15] Carl Svärd, Mattias Nyberg, and Erik Frisk. A greedy approach for selection of residual generators. 22nd International Workshop on Principles of Diagnosis (DX-11), Murnau, Germany, 2011.

[C16] Mattias Krysander, Jan Åslund, and Erik Frisk. A structural algorithm for finding testable sub-models and multiple fault isolability analysis. 21st International Workshop on Principles of Diagnosis (DX-10), Portland, Oregon, USA, 2010.

[C17] Erik Frisk, Anibal Bregon, Jan Åslund, Mattias Krysander, Belarmino Pulido, and Gautam Biswas. Diagnosability analysis considering causal interpretations for differential constraints. 21st International Workshop on Principles of Diagnosis (DX-10), Portland, Oregon, USA, 2010.

[C18] Erik Almqvist, Daniel Eriksson, Andreas Lundberg, Emil Nilsson, Niklas Wahlström, Erik Frisk, and Mattias Krysander. Solving the ADAPT benchmark problem - A student project study. 21st International Workshop on Principles of Diagnosis (DX-10), Portland, Oregon, USA, 2010.

[C19] Erik Höckerdal, Erik Frisk, and Lars Eriksson. Model based engine map adaptation using EKF. In *6th IFAC Symposium on Advances in Automotive Control*, Munich, Germany, 2010.

[C20] Christofer Sundström, Erik Frisk, and Lars Nielsen. Overall monitoring and diagnosis for hybrid vehicle powertrains. In *6th IFAC Symposium on Advances in Automotive Control*, Munich, Germany, 2010.

[C21] Emil Larsson, Jan Åslund, Erik Frisk, and Lars Eriksson. Fault isolation for an industrial gas turbine with a model-based diagnosis approach. In *ASME Turbo Expo 2010-GT2010*, Glasgow, UK, 2010. ASME.

[C22] Albert Rosich, Erik Frisk, Jan Åslund, Ramon Sarrate, and Fatiha Nejjari. Sensor placement for fault diagnosis based on causal computations. In *Proceedings of IFAC Safeprocess'09*, Barcelona, Spain, 2009.

[C23] Jan Åslund and Erik Frisk. Structural analysis for fault diagnosis of models with constraints. In *Proceedings of IFAC Safeprocess'09*, Barcelona, Spain, 2009.

[C24] Mattias Krysander, Fredrik Heintz, Jacob Roll, and Erik Frisk. Dynamic test selection for reconfigurable diagnosis. 47th IEEE Conference on Decision and Control, Cancun, Mexico, 2008.

[C25] Fredrik Heintz, Mattias Krysander, Jacob Roll, and Erik Frisk. FlexDx: A reconfigurable diagnosis framework. 19th International Workshop on Principles of Diagnosis (DX-08), Sydney, Australia, 2008.

[C26] Erik Höckerdal, Lars Eriksson, and Erik Frisk. Air mass-flow measurement and estimation in diesel engines equipped with EGR and VGT. In *Electronic Engine Controls*, number 2008-01-0992 in SAE Technical paper series SP-2159, SAE World Congress, Detroit, USA, 2008.

[C27] Esteban R. Gelso, Erik Frisk, and Joaquim Armengol. Robust fault detection using consistency techniques with application to an automotive engine. IFAC World Congress, Seoul, Korea, 2008.

[C28] Erik Frisk and Mattias Krysander. Leakage detection in a fuel evaporative system. IFAC World Congress, Seoul, Korea, 2008.

[C29] Erik Höckerdal, Erik Frisk, and Lars Eriksson. Observer design and model augmentation for bias compensation applied to an engine. IFAC World Congress, Seoul, Korea, 2008.

[C30] Fredrik Gustafsson, Jan Åslund, Erik Frisk, Mattias Krysander, and Lars Nielsen. On threshold optimization in fault tolerant systems. IFAC World Congress, Seoul, Korea, 2008.

[C31] Mattias Krysander, Erik Frisk, and Jan Åslund. Sensor placement for fault isolation in linear differential-algebraic systems. IFAC World Congress, Seoul, Korea, 2008.

[C32] Erik Frisk and Mattias Krysander. Sensor placement for maximum fault isolability. 18th International Workshop on Principles of Diagnosis (DX-07), pages 106–113, Nashville, USA, 2007.

[C33] Erik Frisk, Mattias Krysander, Mattias Nyberg, and and Jan Åslund. A toolbox for design of diagnosis systems. In *Proceedings of IFAC Safeprocess'06*, Beijing, China, 2006.

[C34] Jonas Biteus, Erik Frisk, and Mattias Nyberg. Distributed diagnosis by using a condensed local representation of the global diagnoses with minimal cardinality. 17th International Workshop on Principles of Diagnosis (DX-06), Spain, 2006.

[C35] Jonas Biteus, Mattias Nyberg, Erik Frisk, and Jan Åslund. Determining a component's fault status and the status' readiness. In *Proceedings of IFAC Safeprocess'06*, Beijing, China, 2006.

3. Monographs

[M1] Erik Frisk. *Residual Generation for Fault Diagnosis*. PhD thesis, Linköpings Universitet, November 2001.

[M2] Erik Frisk. Residual generation for fault diagnosis: Nominal and robust design. Technical report, 1998. LiU-TEK-LIC-1998:74, Thesis No. 739.

5. Book chapters

[B1] Erik Höckerdal, Lars Eriksson, and Erik Frisk. *Off- and On-Line Identification of Maps Applied to the Gas Path in Diesel Engines*, volume 418 of *Identification for Automotive Systems, In Lecture Notes in Control and Information Sciences. Editors: D. Alberer, H. Hjalmarsson and L. del Re.*, pages 241–256. Springer Verlag, 2012.

6. Patents

[P1] Mattias Nyberg, Jonas Bitéus, Erik Frisk, and Jan Åslund. Fault diagnosis. US patent, US7809986. Oct 5, 2010.

[P2] Mattias Nyberg, Jonas Bitéus, Erik Frisk, and Jan Åslund. Fault diagnosis. EU patent, EP1895377. Dec 10, 2008.

7. Software

[S1] Erik Frisk and Mattias Krysander. SensPlaceTool - A Matlab tool for sensor placement for fault diagnosis. `http://www.fs.isy.liu.se/Software/SensPlaceTool/`.

[S2] Erik Frisk and Mattias Krysander. LinSensPlaceTool - A Mathematica tool for sensor placement for fault isolation in linear DAE:s. `http://www.fs.isy.liu.se/Software/LinSensPlaceTool/`.

[S3] Erik Frisk and Mattias Krysander. CausalIsolability - A Matlab tool for fault isolability analysis. `http://www.fs.isy.liu.se/Software/CausalIsolability/`.

[S4] Mattias Krysander and Erik Frisk. TestModTool - A Matlab tool finding testable models. `http://www.fs.isy.liu.se/Software/TestModTool/`.

CV

Name: Erik Frisk	**Doctorial degree:** 2001-11-20
Birthdate: 19711130	**Academic title:** Docent
Gender: Male	**Employer:** No current employer

Research education

Dissertation title (swe)
Residualgenerering för feldiagnostik

Dissertation title (en)
Residual generation for fault diagnosis

Organisation	Unit	Supervisor
Linköpings universitet, Sweden Sweden - Higher education Institutes	Institutionen för systemteknik (ISY)	Lars Nielsen

Subject doctors degree	ISSN/ISBN-number	Date doctoral exam
20202. Reglerteknik	ISSN 0345-7524/ISBN 91-7373-115-3	2001-11-20

Publications

Name: Erik Frisk	**Doctorial degree:** 2001-11-20
Birthdate: 19711130	**Academic title:** Docent
Gender: Male	**Employer:** No current employer

Frisk, Erik has not added any publications to the application.

Register

Terms and conditions

The application must be signed by the applicant as well as the authorised representative of the administrating organisation. The representative is normally the department head of the institution where the research is to be conducted, but may in some instances be e.g. the vice-chancellor. This is specified in the call for proposals.

The signature*from the applicant*confirms that:

- the information in the application is correct and according to the instructions form the Swedish Research Council
- any additional professional activities or commercial ties have been reported to the administrating organisation, and that no conflicts have arisen that would conflict with good research practice
- that the necessary permits and approvals are in place at the start of the project e.g. regarding ethical review.

The signature *from the administrating organisation* confirms that:

- the research, employment and equipment indicated will be accommodated in the institution during the time, and to the extent, described in the application
- the institution approves the cost-estimate in the application
- the research is conducted according to Swedish legislation.

The above-mentioned points must have been discussed between the parties before the representative of the administrating organisation approves and signs the application.

Project out lines are not signed by the administrating organisation. The administrating organisation only sign the application if the project outline is accepted for step two.

Applications with an organisation as applicant is automatically signed when the application is registered.