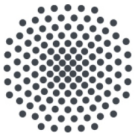

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Master's Thesis

Host-based Intrusion Detection to enhance Cybersecurity of Real-time Automotive Systems

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To Family and Love.
Endless inspiration, admiration and strength.
Dears Dragana, Miroslav, Nikola and Aleksandra

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This Master Thesis is the crown of my Master Degree. For past 2 years, I went to many different experiences by studying and living abroad. The journey of one epoch ends here and starts the new one. Enormous gratitude I owe to my dear parents Dragana and Miroslav and beloved brother Nikola. The greatest support, strength and power through best and worst is my beloved Aleksandra. Love and Family are the greatest values that can enrich the man. Thanks to them I am complete and now I have finished great Chapter of my career, of my studies.
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Abstract

Modern automotive industry develops technology advancing vehicles in direction of interconnectivity. Estimation forecast [1] shows that by 2025, more than 470 million vehicles will be connected among each other, to Smart-Roads, Smart-Homes, etc. Due to external communication of a car to surrounding, the vehicle is under the exposure to potential attacks through those communication channels. The attack case from 2015. by C. Miller and C. Valasek [2] shows what could happen if modern vehicles are not protected from external malicious/non-verified access. In order to detect an attack, an Intrusion Detection System (IDS) is used. However, the future attacks cannot be predicted, and thus IDS are run to detect anomalies in the system behavior. IDS can be separated into two main fields: Communication channels monitored by Network-based IDS and Control Units monitored by Host-based IDS. The scope of the Thesis is detecting anomalies of behavior of a Control Unit within the vehicle based on timing elements of its functions. The method proposed by this Thesis is called *AutoSec* - Host-based Intrusion Detection System. The goal of *AutoSec* is, in compliance with AUTOSAR standard, to reach high detection rate of Anomalies in the system, by keeping level of False Alarms close to zero.

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List of Abbreviations

AUTOSAR	AUTomotive Open System ARchitecture
ADAS	Advanced driver-assistance systems
AGL	Automotive Grade Linux
ABS	Anti-lock Braking System
ASIL	Automotive Safety Integrity Level
AP	Affinity Propagation
BSW	Basic Software
CAN	Controll Area Network
CDD	Complex Driver(s)
CNN	Convolutional Neural Network
CPU	Central Processing Unit
DBSCAN	Density-based spatial clustering of applications with noise
ECU	Electronic Control Unit
ES	Embedded Systems
ECUAL	Electronic Control Unit Abstraction Layer
E/E	Electric and Electronic
EDF	Earliest Deadline First
FPGA	Field-programmable gate array
FP	False Positive
FPR	False Positive Rate
FN	False Negative
GMM	Gaussian Mixture Model

HB	Host-based
HIDS	Host-based Intrusion Detection System
HW-HB-IDS	Hardware-Oriented Host-Based Intrusion Detection System
IoT	Internet of Things
ISR	Interrupt Service Routine
IDS	Intrusion Detection System
KNN	k-Nearest Neighbours
ML	Machine Learning
MCAL	Microcontroller Abstraction Layer
MCU	Micro Control Unit
MDD	Model Driven Development
NB	Network-based
NIDS	Network-based Intrusion Detection System
NN	Neural Network
OEM	Original Equipment Manufacturer
OS	Operating System
PCA	Principal component analysis
RT	Real-Time
RTS	Real-Time System
RTOS	Real-Time Operating System
RTE	Real-Time Environment
RM	Rate Monotonic
SWC	Software Component
VFB	Virtual Functional Bus
S2S	Start-to-Start
SW-HB-IDS	Software-Oriented Host-Based Intrusion Detection System

TDD Test Driven Development

TIMEX Timing Extensions

TP True Positive

TPR True Positive Rate

TN True Negative

WDM Watchdog Manager

WCET Worst-Case Execution Time

Chapter 1

Introduction

Modern life experiences rapid evolution and sudden changes on daily basis. Technological capabilities are there to help us while residing in the background of our lives. Looking back into last 2 decades, we can observe an influence of technology. 20 years back, mobile network had very little coverage in comparison to today's capabilities. 10 years later, the first smart phones started becoming part of our lives. Today we witness a new element that is about to become the next part of us.
Upcoming 5G mobile network brings new technological innovations resulting in a multi-billion number of interconnecting devices. Considering part of these devices is related to the transportation system, mainly new "smart" cars with autonomous driving systems, "smart" roads, etc. According to Ericsson, one of the biggest telecommunication vendors in the World, around 400 million devices have been interconnected with cellular connection as part of Internet of Things (IoT). Furthermore, the number of these devices exponentially grows and estimations show that the number of networked devices will overcome 1.5 billion by 2022 [11]. Personal transportation vehicles are part of this network and we can already get hands on one of those state-of-art vehicles, such as Tesla - *Connectivity*, Mercedes-Benz - *me connect*, BMW - *Connect Drive*, etc. The main focus is rather way broader than only a connection to the Network. News as [12] confirm merging actions of multiple Automotive Original Equipment Manufacturer (OEM)s, regarding services based on inter-connectivity.

1.1 General Problem Statement

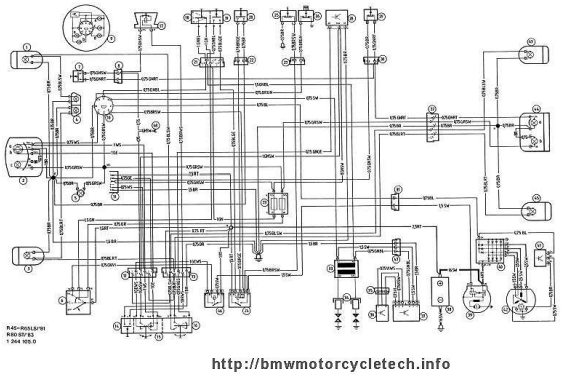
Considering the automotive industry, when it comes to vehicles and passengers, the safety is the top priority. One of the most important standards is **ISO26262**, titled **"Road vehicles – Functional safety"**, being the core of modern automotive industry [13]. In order to enhance the safety of passengers while enriching their drive comfort, vehicle-to-vehicle (known as V2V), or generally speaking Car2X (car-to-many), is there to interconnect the traffic and support sharing of valuable information about the surrounding, road cases, safety warnings, etc. The topic of Car2X is discussed in [14], followed by an example regarding the average drivers' reactions and the travelled distance during this short time. Driver's reaction time is defined as the time between when the event has been observed and the time at which the driver actually reacts. Typical reaction time is in the range from 0.75 to 1.5 s [15]. The traveled distance during the reaction time, at the speed of 110 km/h, is between 23 and 46 m. Hence,

the need for connecting cars in order to improve safety systems, increases. Side effect results in opening modern vehicles' systems to be exposed to external threats from cyberattacks.

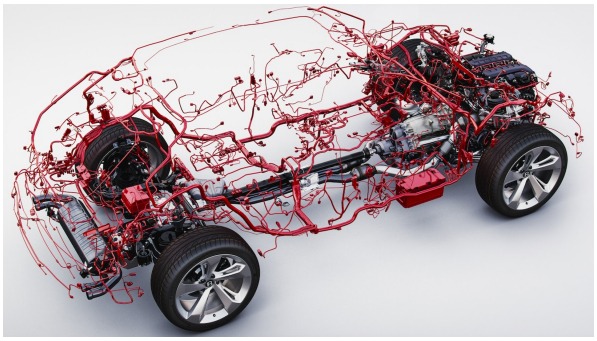
1.2 Motivation

Historically, very first cars had close to nothing technicalities related to the electronics, apart from basic wiring harnesses. One of the examples can be seen in the Figure 1.1a, where the wiring harnessing for BMW R65 is presented. Fundamentally, the only electronics necessarily needed for running the car are related to engine and accumulator connections. However, safety in traffic and commuting raised concerns and at first, turning signals have been added, then wipers, etc. Additional safety measures and comfort features and systems raised the complexity level of wiring systems in modern cars. The complexity, only of wiring, has been showed in the Figure 1.1b.
According to [16], premium cars in 2010 had up to 70 Electronic Control Unit (ECU), while today this number has gone beyond 100. The ECU is a computational unit that is in charge of specific control and handling of a vehicle elements, such as engine control, suspension control, driver assistance (i.e. Advanced driver-assistance systems (ADAS)), etc. Thus, considerable level of innovations (90%) in automotive industry is driven by electronics and software. Therefore, the development costs of electronics and software are going up to 40% of all costs, while 50-70% of these costs are invested in software for ECUs.
Considering this amount of control units (ECUs), we have a distributed multivariable system. These units used to communicate over Controll Area Network (CAN), developed in '80s specifically for automotive industry. With increased number of data needed for complex control and calculations, modern cars implement Ethernet communication as well. All of this has made modern vehicles to be considered as big computational units. Due to this high level of complexity and dependencies, a partnership between main OEMs and Tier1 suppliers has been organized to standardize modern vehicle architecture. The AUTOSAR has been grounded in 2002-2003 [17]. The first release AUTOSAR Classic Platform Release 1.0 was in 2005. More about AUTOSAR will be discussed in the Chapter 2 - Section 2.1.1 AUTOSAR.
Due to increasing number of safety systems and their complexity, there is a high internal communication overhead. Influenced by IoT and interconnectivity requirements, the internal communication in cars has been exposed to attackers more than ever. The most well known an attack on a vehicle network has been performed by Charlie Miller and Chris Valasek [2]. They have breached into the vehicle network and interfered the messages payloads. By these doings, Miller and Valasek were able to completely overtake the control over the vehicle. The greatest concern was that they have been able to override drivers action remotely through wireless network by being many kilometers away from the vehicle.
Following this event, many OEMs started rapid investments in security measures of vehicle's electronics and software, resulting in increasing number of researches about Intrusion Detection System (IDS). The scope of vehicle protection is not only based on protecting communication between ECUs, but also to protect internal components and integrity of each ECU separately. The main classification of IDS is based on whether a Network/Communication is monitored - Network-based (NB) Intrusion Detection System; or a internal operations of

ECU is being monitored - Host-based (HB) Intrusion Detection System. More about the IDS will be discussed in the following Chapter 2 - Section 3.1.



(a) BMW R65-wiring harnesses[1]



(b) Bentley Bentayga-wiring harnesses[2]

Figure 1.1: Wiring Harnesses through history of Automotive industry

1.3 Thesis overview

Starting from vehicles' safety, an automotive industry needed to introduce security measures as well. Therefore safety and security has become a unique element that is the backbone of modern vehicles. In following figures 1.2 and 1.3 we can observe how Safety&Security is moving from being only mid-term priorities towards the right upper-corner, to be also an element in short-term priorities as a part in ever evolving agile model of development.
The scope of this thesis is security measures as Anomaly and Intrusion Detection System of the AUTOSAR System. The main field of research and proposed algorithm is related to the Host-Based IDS. In the following Chapter 2 - Background on AUTOSAR and Embedded Systems will be given. In addition, in Chapter 3 - Related Work covers prior work related to IDS. The research in the IDS field will be examined and presented. Regarding the AUTOSAR Architecture and ECU behaviour, there are possible approaches:

- **SysCall - System Call** approach: based on the statically analyzed code, a control flow and function calls in the ECU will be monitored to detect possible unexpected behaviour. More about this model in Section 3.2 about Host-based IDS.
- **Machine Learning (ML)** approach: using machine learning techniques to *learn* a ML model based on input dataset of ECU's behavior model.
- **AUTOSAR Embedded Systems (ES) Elements** approach: to monitor ECU's ES

[1]source: http://bmwmotorcycletech.info/
[2]source: https://www.motor1.com/news/65202/bentley-bentayga-wiring-harness-is-weirdly-beautiful/

elements and features to detect non-deterministic behaviour and examine nature of the anomaly. Generally speaking, to detect whether the anomaly is a graceful degradation of the system or intrusion and potential attack.

The main contribution of the thesis is oriented into developing algorithm based on the 3rd approach - AUTOSAR ES Elements. In the Chapter 4 - Design Concept, the approach for an anomaly will be defined and details will be discussed.

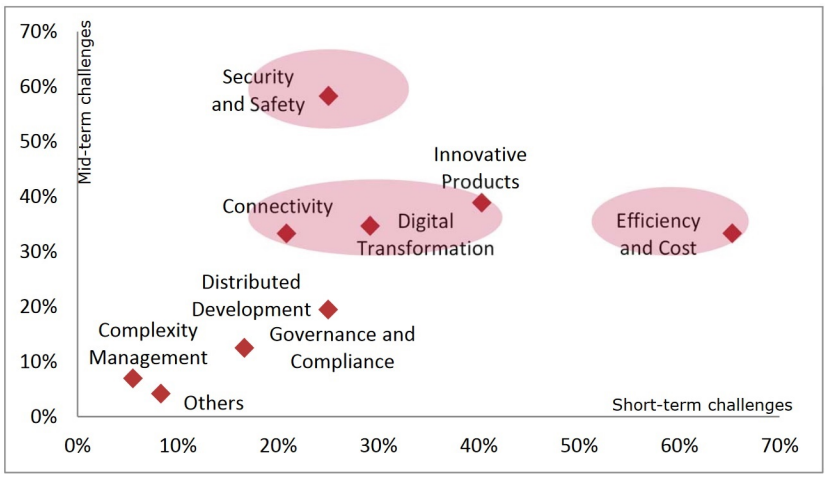


Figure 1.2: Vector Client Survey 2017[3]

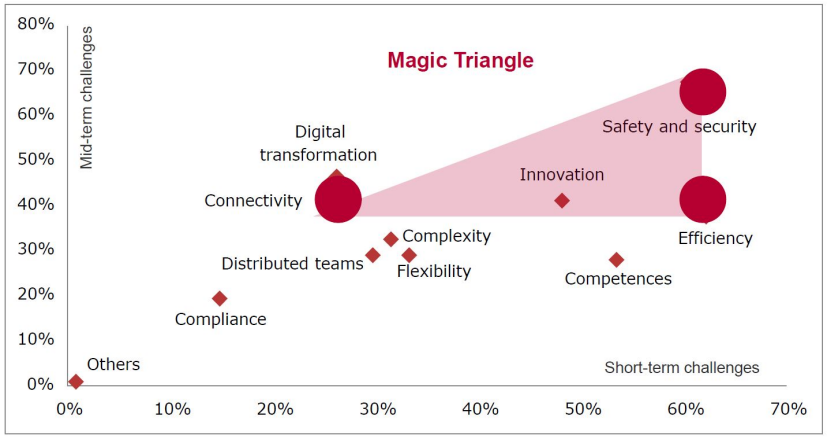


Figure 1.3: Vector Client Survey 2018[4]

[3] Details: www.vector.com/trends. Horizontal axis shows short-term challenges; vertical axis shows mid-term challenges. Sum > 100% due to 3 answers per question. Strong validity with > 4% response rate of 1500 recipients from different industries worldwide.

[4] Details: www.vector.com/trends. Horizontal axis shows short-term challenges; vertical axis shows mid-term challenges. Sum > 200% due to 5 answers per question. Strong validity with > 4% response rate of 2000 recipients from different industries worldwide.

1.4 Thesis Contribution

The Thesis proposes the novel Host-based Intrusion Detection method for Real-Time automotive systems, called ***AutoSec*** - AUTOSAR Security. The contribution of the Thesis through ***AutoSec*** method are briefly listed:

- novel Host-based Intrusion Detection based multiple timing features
- AUTOSAR compliant
- Semi-automatized approach for training on large number of tracing (measuring) points
- Real-World Environment applicability
- Multiresolution tracing
- Multilevel of degree of Anomaly
- Evaluation of large number of clustering methods

Prior to method proposal, the research has been conducted in the field of Intrusion Detection Systems as well as modern architecture of Embedded Systems in the Automotive Industry under the AUTOSAR Standard. The proposed method, *AutoSec*, uses multiple different timing features and those features could be used on any tracing block within the program. Thus, *AutoSec* provides broad spectrum of applicability on Real-Time Systems on many different independent elements within.
More about each of these points will be discussed through out upcoming Chapters, mainly in Chapter 4.

Chapter 2

Background

The transportation and commuting has become important part of our lives. Therefore, the automotive industry is developing high measures of safety and nowadays security measures for modern vehicles. In addition, in order to make commuting comfortable and extremely pleasant, new technologies for autonomous driving are in a fast development process. As described in [18], the automotive industry has an aim to replace human perception of the environment. Thus, the modern technologies as high-resolution radar and video sensors are essential in order to bring new driver assistance systems in use. Due to high sensor resolutions and high data sampling rate, excessive amount of data has been transported via vehicle's communication networks. In addition to communication, all the data needs to be processed in real-time so the needed and required safety is guaranteed. Many different challenges in this complex architecture [19] occurs and they need to be standardized. The main focus today is as discussed in Section 1.2 - Motivation.
ADAS is the main component in today's vehicles which ensures the assistance to the driver and ease of driving while guarantying safety of all passengers and other actors in the surrounding. The most common safety elements are: ACC - Adaptive Cruise Control, LDW - Lane Departure Warning, EBA - Emergency Brake Assist, BSD - Blind Spot Detection, RCTA - Rear Cross Traffic Alert, etc. The extreme number of vast sensors and actuators require high computational power and control to ensure given requirements, especially in terms of safety.

2.1 Operating Systems

Based on the requirements, a deterministic system with time constraints is needed to ensure designed control and data flow needed for safety guarantees. Thus, ES as Real-Time System (RTS) are widely used in automotive industry to provide needed determinism. More about Real-Time (RT) Systems and Constraints, refer to Section 2.2 - Real-Time Systems. With the complexity of vehicle's Electric and Electronic (E/E) Systems, ES needed standardization in automotive industry. Many vehicle manufacturers use Automotive Grade Linux (AGL) as underlying Operating System (OS) to ensure Real-Time Constraints. Some other OEMs use Real-Time Operating System (RTOS) such as *QNX*, *FreeRTOS*, *OpenRTOS*, etc.
However, standardized automotive architecture is AUTOSAR - AUTomotive Open System ARchitecture. AUTOSAR is an alliance of OEMs, Tier1 suppliers, semiconductor manufacturers, software suppliers, tool suppliers and others organized to establish an open industry

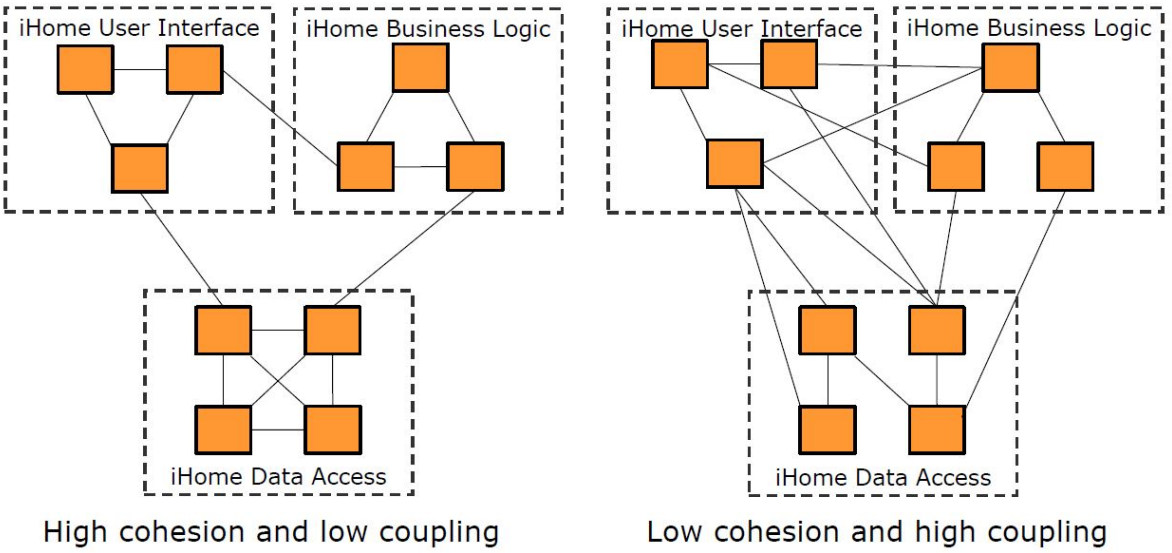


Figure 2.1: Cohesion vs Coupling of software structure [3] - slide 326

standard for an automotive software architecture. The main purpose is to define a basic infrastructure for the management of functions within both future applications and standard software modules [17].

2.1.1 AUTOSAR

In 2003, automotive OEMs, Tier1 suppliers and related manufacturers and suppliers joined on the mission to develop the basis of future software for ECUs in vehicles - AUTOSAR. The aim is to create a backbone for collaboration on basic functions, whilst excluding certain functional components of higher level of abstraction. The components were left out for making a competitiveness in development and innovations, between different suppliers, in terms of new functions and features. The core advantage of AUTOSAR is an ability to flexibly distribute software into ECUs, independently of a ECU supplier or hardware architecture.
Summing up, as explained in [4], AUTOSAR goals are as follows:

- Standardization of interfaces between functions of the application software and to basic functions
- Definition of a reference architecture for ECU software
- Standardization of exchange formats for distributed development processes

Since automotive industry has dominant attributes of innovation and competitiveness, there are multiple benefits introduced by using AUTOSAR:

- Ability to optimize the ECU network by flexible integration, relocation and exchange of

functions

- Mastery over increasing product and process complexity
- Maintainability over entire product life cycle

By excluding specifications and requirements regarding certain components in AUTOSAR due to competitiveness and innovations, the AUTOSAR standard lacks the capability of describing the functional behavior of a software components. Contrary to being a disadvantage, this lack of capability helps to reach higher modularity. As explained in [3], the main goal of modularity is **high cohesion and low coupling** of the software structure. With respect to the code units, cohesion represents intramodule connectivity and coupling represents intermodule connectivity - Figure 2.1. Since 2003, AUTOSAR Alliance has released 4 versions, called Releases. The year and a release version of AUTOSAR can be followed through the Figure 2.2. Meanwhile, AUTOSAR Version 3.0 was the first release used in production line ECUs.

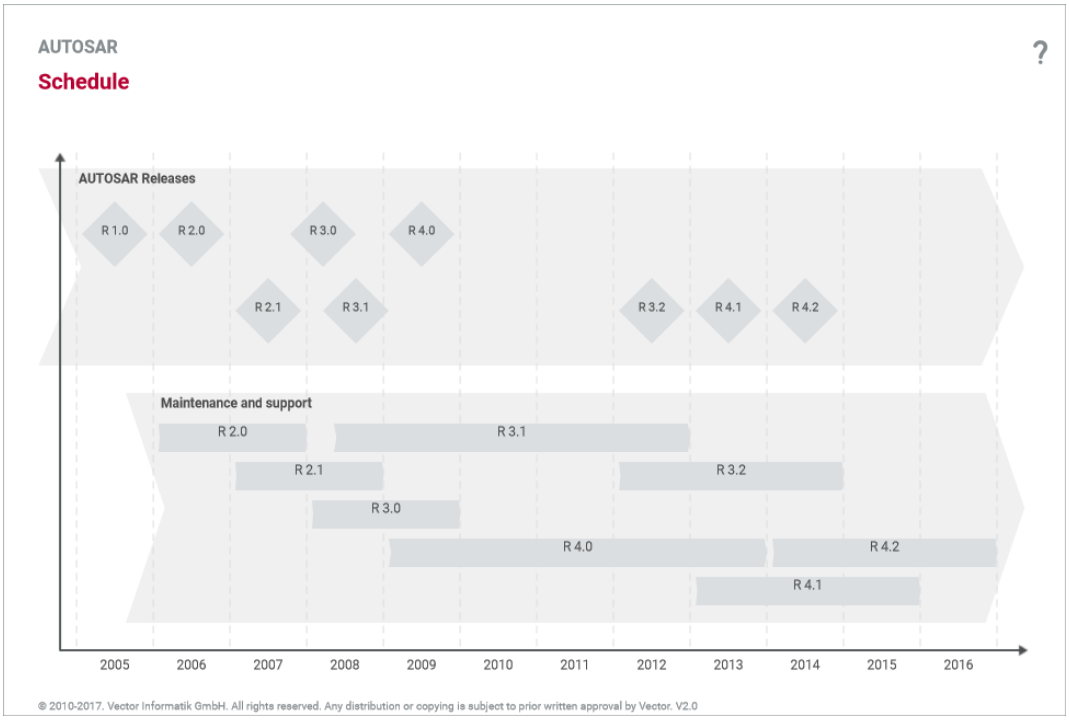


Figure 2.2: AUTOSAR Releases[1]

[1]source: https://elearning.vector.com/mod/page/view.php?id=439

2.1.1.1 Concept

AUTOSAR specifications, templates, requirements and other related documents can be found on the official page of alliance - AUTOSAR Official Website. According to general specification of the AUTOSAR, the Architecture distinguishes on the highest abstraction level between three software layers: Application, Real-Time Environment (RTE) and BSW which run on a Microcontroller or Microcontroller Abstraction Layer (MCAL), as presented in the Figure 2.3 [5].

- Application Layer - OEM defined applications and use cases, i.e. Anti-lock Braking System (ABS), control of Daytime Lights, control of Windows on doors, etc.
- RTE - abstracts the application layer from the basic software. It controls the runtime behavior of the application layer and implements the data exchange [4].
- BSW - many predefined modules that are grouped into layers. For detailed structure and organization of BSW refer to Section 2.1.1.2.
- Microcontroller Layer - specific firmware dependent on ECU architecture. It is provided by hardware vendors.

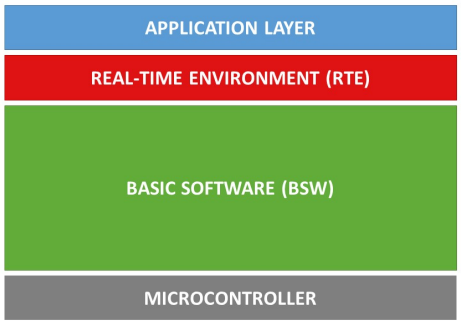
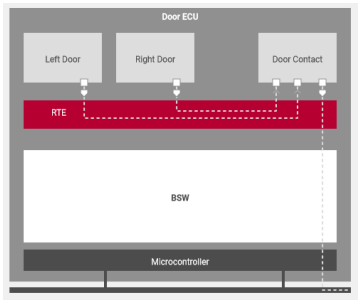


Figure 2.3: AUTOSAR Layered architecture organization - simplified representation

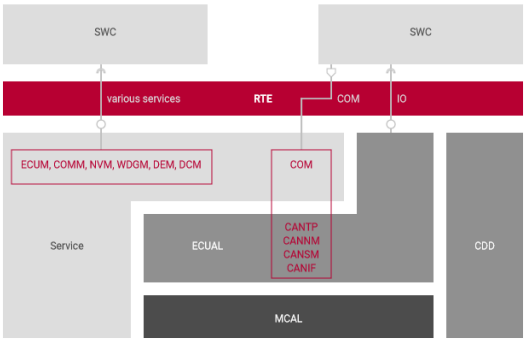
2.1.1.2 Architecture

Through this section, two main Layers will be considered - Application Layer and Basic Software Layer. As it will be discussed in Chapter 3 and 4, elements and features of these two layers will be used.
Having an insight on more fine-granular level, the Application Layer consists of different Applications. As it could be seen in the Figure 2.4a (different applications are *Left Door*, *Right Door* and *Door Contact*. In the first steps during a design, the functional software of the vehicle is described in a high abstraction layer, as it could have been seen in the

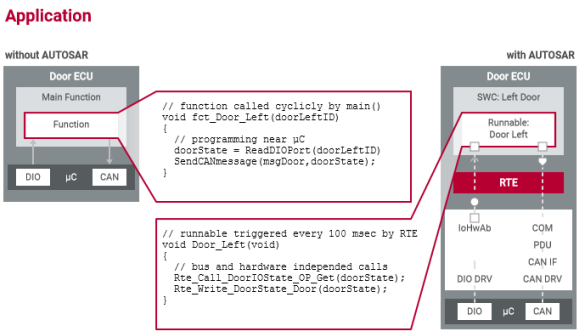
Figure 2.4a. Following next lower level of abstraction, the overall system is divided into sub-functionalities. Mainly, each of this applications consists of different functional blocks called Software Component (SWC) - Figure 2.4b.
Applications does not necessarily consists of a single SWC but rather of multiple SWC. A SWC can be either SWC-Composition or SWC-Atomic. The difference is that Atomic could not be further divided in terms of functionalities, while Composition consists of other SWC-Compositions and/or SWC-Atomics.
Having a look into the structure of a SWC, building blocks of a SWC are called Runnables (Runnable Entities). In other words, as described in [4], Runnable Entity is the execution unit, which is finally implemented as a *C* function, as it is depicted in Figure 2.4c. The function calls to the Runnable Entities are configured by the developer, and later implemented by the RTE. This might, for example be periodic or spontaneously in response to receiving a data element.
The distinctive feature of SWC is the communication abstraction between multiple SWCs through interfaces. The Data is transmitted through RTE over Virtual Functional Bus (VFB) to some other SWC(s). The communication interfaces provide Ports as an "attaching" elements for a communication between multiple entities. The Port description is agreed prior to the design of SWC, so all developers of different Applications know the Communication Policies. Mainly, AUTOSAR distinguish between two different methods of communication: *Sender-Receiver* and *Client-Server*. For more about these methods refer to [20].



(a) Applications example



(b) Mappings to SWC



(c) SWC mapped on Runnables

Figure 2.4: AUTOSAR - Application Layer [4]

As it will be discussed in the following Section 2.3, Application Layer is OEM dependent, while BSW is provided and designed by the specific vendor of AUTOSAR. The layer model simplifies porting of software to different hardware. Previously, such porting required extensive adaptations at various points all the way up to the application layer in the case of poorly designed software architectures. Using AUTOSAR, all what needs to be done is to replace all microcontroller specific drivers in the MCAL. The modules in the ECU abstraction layer just need to be reconfigured whilst all other layers not being affected by porting. This significantly reduces implementation and testing effort as well as associated risk. The main course of this Thesis is to cover safety of the system from the point of BSW. Basic Software can be divided into four main components [5], as presented in the Figure 2.5.

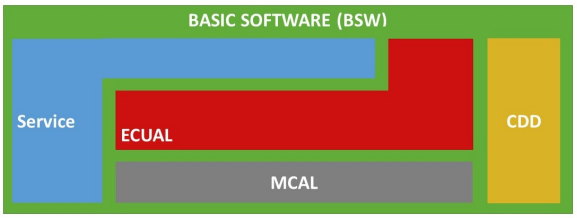


Figure 2.5: BSW Structure [5]

The Service Layer presents the highest layer of the Basic Software whose task is to provide basic services for Applications, RTE and Basic Software Modules. Services provided by this sub-layer reflect standardized services related to Operating System, Memory, Network communication, etc. The main Services are: System Service, Memory Services, Crypto Services, Off-board Communication Services, Communication Services.
The Electronic Control Unit Abstraction Layer (ECUAL) offers uniform access as an interface to MCAL, all functionalities of an ECU such as communication, memory or IO – regardless of whether these functionalities are part of the microcontroller or are implemented by peripheral components. The target of this layer is to make higher software layers independent of ECU hardware layout.
The Microcontroller Abstraction Layer (MCAL) is the lowest software layer in the BSW as a layer containing internal drivers for direct access to microcontroller and internal peripherals, such as: access to memory, communication, input/output (IO) of the microcontroller, etc. The goal is to make higher software layers independent of microcontroller
The Complex Drivers Layer (Complex Driver(s) (CDD)) spans from the hardware to the RTE. The CDD layer is a special case for special purpose functionalities, as drivers for devices, that are not specified within AUTOSAR, for migration purposes, or for drivers with **very high timing constraints**.

2.2 Real-Time Systems

System Engineering is highly broad field of study. Mainly, if the system needs to be always on and ready to react on external stimulus, the system is considered Real-Time System. The explanation of Real-Time systems is given in [6]. The Real-Time systems are not about systems that depend only on a value or data, but rather depending more on those values being on time as for calculation processes being executed in time. A reaction happening too late could lead to severe consequences. Severity in this context is related to safety of the system. More about Safety and Security of such systems will be discussed in following Section 3.1. The definition of Safety and Security is given in [21]:

- **Definition of Safety**: "*Safety is the state of being 'safe' (from French sauf), the condition of being protected from harm or other non-desirable outcomes*"
- **Definition of Security**: "*A system is secure if it is protected against harm caused by attacks originating from outside the system.*"

Depending on timing criticality, a system can be Soft- or Hard-Real Time System. The main difference is in severity of consequences if a deadline of a task in the real-time system has been missed. In order to secure the constraints of Safety and Security, Real-Time computations is needed. More about Timings in Real-Time Systems will be discussed in the following Section 2.2.2. The ubiquitous presence of Real-Time Embedded Systems within everyday applications that we use will be presented in Section 2.2.4 as part of the motivations of this Thesis.

2.2.1 Fundamentals of Real-Time Embedded Systems

The wide range of today's applications are developed as Real-Time systems due to high need of different in time processes. Timing criticality, in order to ensure Safety&Security, needs deterministic behaviour and high level of certainty in execution context. The certainty in execution is being guarded by specifying ***Deadlines***. Depending on the Deadline, soft and hard deadlines can be distinguished, differentiating a Soft Real-Time System from the Hard Real-Time System. The definition of hard deadline as a time constraint is [21]:

- **Definition of Time Constraint**: "*A time constraint is called **hard** if not meeting that constraint could result in a catastrophe.*"

Each system consists of different states of the executions, applications, elements, processes, etc. One of the examples is given in previous Chapters as the Control Systems in Automotive Industry and AUTOSAR being one of the elements of a system, of the vehicle. A process is a computation executed on the processor. The process as a logical unit with specified goal to be executed is called ***Task***. During a lifetime of a system, the Task will be executed indefinite number of times. Each instance of a Task is called ***Job***. The order of Jobs, meaning the order of Tasks' executions is calculated using a ***Scheduler***. A scheduler is a computational unit

which calculates when an instance of a Task will be scheduled for an execution. The calculation is based on timing constraints of Tasks and also dependent on a scheduling algorithm. More about specifics regarding Tasks, Jobs and Scheduler refer to [21]. In the following chapters, the elements that will be discussed are related to the understanding of the AUTOSAR OS and *AutoSec*, an intrusion detection concepts proposed in this Thesis.
In this section, tasks and tasks' timings used for designing an embedded system will be discussed. Firstly, a different types of tasks need to be differentiated. Mainly, depending on the nature of the Task, we differ three types of Tasks [6]:

- **Periodic Task** - tasks in embedded systems are commonly periodic, meaning that each task has the period of execution. The example is sampling data from a sensor. The required sampling rate is 1kHz, therefore a Task that reads sensor data will be triggered/called every 1/1kHz = 1ms.

- **Sporadic Task** - not as common as periodic tasks in embedded systems. The sporadic tasks usually do not have the period of execution, but rather an expected minimum interarrival time, meaning only probability of time between two instances of the sporadic task is specified. The example, occasional checkup of the system network, driven by some internal or external events, timeouts or actions.

- **Aperiodic Task** - the aperiodic task is very similar to the sporadic task, but the difference is that the aperiodic tasks do not have specified minimum interarrival time. The aperiodic task are only a specific reaction to the certain action in the system. The example could be: activation of the ABS in the car, or activation of Air-Bags in the car when a collision occurs.

During the design time, for each task an execution time will be calculated, usually based on Worst-Case Execution Time (WCET) calculations. By knowing expected execution time and a period of periodic tasks, an overall expected Central Processing Unit (CPU) load - processor utilization can be calculated [6], as shown in the equation:

$$U = \sum_{i=1}^{n} \left(\frac{c_i}{p_i} \right) \tag{2.1}$$

In the Equation 2.1, n is the number of tasks mapped to the processor, while e_i is the execution time of a certain task and p_i is the period of that task. In the literature, execution time can be also denoted as C_i or c_i as a computation time of a task, while a period can be denoted as T_i as task execution.
In a system, processes are not equally important for the functionality of a system. The example in automotive industry could be: controlling values for proper engine functioning is more important than sending the control value for turning signal at the same given moment. Therefore, if two tasks are ready to be executed at the same time, a more important task has higher priority. Due to that fact, each task has its priority level denoted as capital P, P_i. Note that order of priority levels depends on the implementation of the OS of Embedded System, i.e. smaller priority number presents higher priority, or vice verse.

Depending on the scheduling algorithm, task priorities can be statically assigned during a design time or dynamically during a runtime. In a case of AUTOSAR, for reaching high level of determinism, a static priority assignment is used. During an execution of a Job, some other Job of higher priority Task can be released for an execution. At that moment, without additional constraints related to resource access controls, the Job of higher priority class, denoted as J_H, will preempt the Job of lower priority Task, denoted as J_L. Thus, the job J_H will start its execution immediately while the job J_L will wait until all jobs of tasks with higher priority have finished their executions, since the job J_H can be furthermore preempted by another job of a task with even higher priority than J_H has. Scheduling concept of task with preemption is given in Figure 2.6. The example of Jobs execution with preemption is presented using Gannt chart approach and it is presented in the Figure 2.7. Note that, in this example, provided by [6], priorities are $P_3 > P_2 > P_1$, where P_3 is priority level of J_3, and the same for jobs J_2 and J_1, respectively. In the lower graph in Figure 2.7, using $\sigma(t)$ is denoted current priority level of a Task being executed.

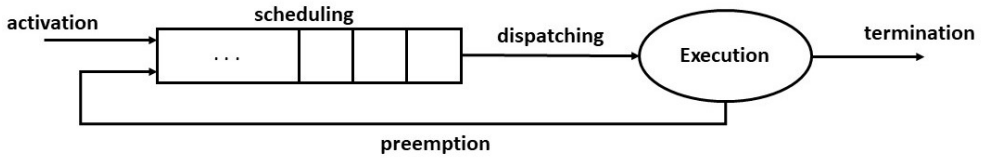


Figure 2.6: Queue of ready tasks waiting for execution[6]

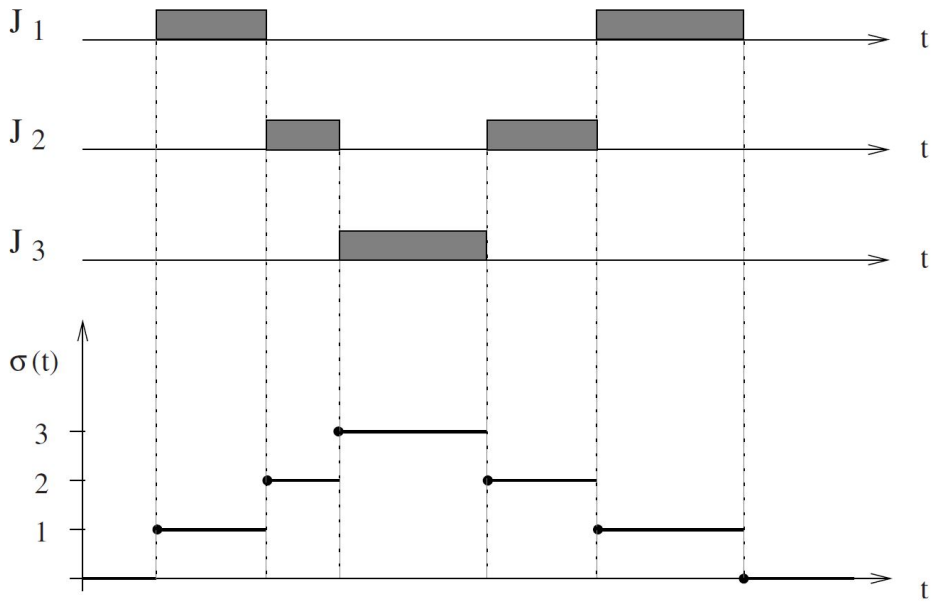


Figure 2.7: Example of a preemptive schedule[6]

However, sometimes preemption can be turned off during a runtime. The occasion of such action is related when a Task has an access to a shared resource, or has an execution of a critical section. The example of a shared resource is a memory, variable in a memory location. In order to keep data consistence, only one Task can have an access to the memory (location) at the time. Regarding the critical section, example could be reading/writing a data stream from/to a communication channel and any interruption of the execution can lead to a communication error or a malfunction, i.e. I2C communication line being blocked[2].
These severity of any ambiguity of the system that can happen during a runtime needs to be considered during a design time. The verification of the system consistency and certainty is done by evaluating timings of the system. Common timings used for the evaluation of the task mappings and determinism of the system will be discussed in the following Section 2.2.2.

2.2.2 Timing constraints of a Task in the Embedded System

As it is discussed in the previous Section 2.2.1, the main characteristic of Real-Time Systems is to be on time. *Deadline* is a typical timing constraint, which presents the most important constraint, presenting a time until a Job of the Task must be executed (completed) so not to cause any safety and/or security violation to the system and surrounding. Deadlines can specified in two ways: *relative deadline* (d_i) - in respect to the task arrival time (explained later in this discussion), and *absolute deadline* (D_i) - when deadline is specified with respect to time zero. While a Task missing a deadline can result in severe consequences, some tasks in the system do not pose high safety risk. As it is specified in the ISO26262 Standard [13], there are four different levels of Safety Integrity: Automotive Safety Integrity Level (ASIL) A, ASIL B, ASIL C and ASIL, while ASIL D dictates the highest level of safety issues and contrary to this, ASIL A sets the lowest level of safety risks. In addition to this, not all tasks have the same level of safety integrity. In general, Tasks are not assigned with ASIL Level, but it is used here rather as an example to draw a parallel between Safety Integrity Level of a System in a vehicle and Deadlines of Tasks that drive that System. As it is presented in [6], depending on the consequences of a missed deadline, tasks distinguish three types of deadlines:

- **HARD**: "*A real-time task is said to be hard if missing its deadline may cause catastrophic consequences on the system under control.*"
- **FIRM**: "*A real-time task is said to be firm if missing its deadline does not cause any damage to the system, but the output has no value.*"
- **SOFT**: "*A real-time task is said to be soft if missing its deadline has still some utility for the system, although causing a performance degradation.*"

In addition to e_i - execution time, p_i - period, and d_i - deadline, a real-time task τ_i can be described using following parameters [6]:

[2]Inter-Integrated Circuit - communication protocol commonly used for communicating with sensors close to the CPU

- **Arrival time** (a_i) or **Release/Requested time** (r_i): is the time at which a task becomes ready for execution;
- **Computation time** ($C_i = \sum_j c_{ij}$): is the sum of all times necessary to the processor for executing the task without interruption;
- **Absolute Deadline** (D_i): is the time before which a task should be completed to avoid damage to the system;
- **Relative Deadline** (d_i): is the difference between the absolute deadline and the request time: $d_i = D_i - r_i$;
- **Start time** (s_i): is the time at which a task starts its execution;
- **Finishing time** (f_i): is the time at which a task finishes its execution;
- **Response time** (R_i): is the difference between the finishing time and the requested time $R_i = f_i - r_i$;
- **Blocked time** ($b_i = \sum_j b_{ij}$): is the sum of all times during a task has not been able to access the shared resource due to the resource being busy by the lower priority task blocking other higher priority tasks to access the shared resource. More about shared resources in Section 2.2.3;
- **Preempted time** ($m_i = \sum_j m_{ij}$): is the sum of all times during a task has been preempted by a higher priority task(s);
- **Criticality**: is a parameter related to the consequences of missing the deadline (typically, it can be hard, firm, or soft);
- **Value** (v_i): represents the relative importance of the task with respect to the other tasks in the system;
- **Lateness** (L_i): $L_i = f_i - d_i$ represents the delay of a task completion with respect to its deadline; note that if a task completes before the deadline, its lateness is negative;
- **Tardiness** or *Exceeding time* (E_i): $E_i = max(0, L_i)$ is the time a task stays active after its deadline;
- **Slack time** or *Laxity* (X_i): $X_i = d_i - a_i - C_i$ s the maximum time a task can be delayed on its activation to complete within its deadline;

However, Tasks are not only driven by timing constraints but also dependent on execution of other Tasks bounded by precedence constraints. Therefore as presented in [6], Tasks cannot be executed in arbitrary order, but precedence relations defined at the design time needs to be respected during a Runtime. Precedence constraints are defined using directed acyclic graph G. Tasks are presented as nodes in the graph, while the task relations are presented using directed branches without creating cycles in the graph.

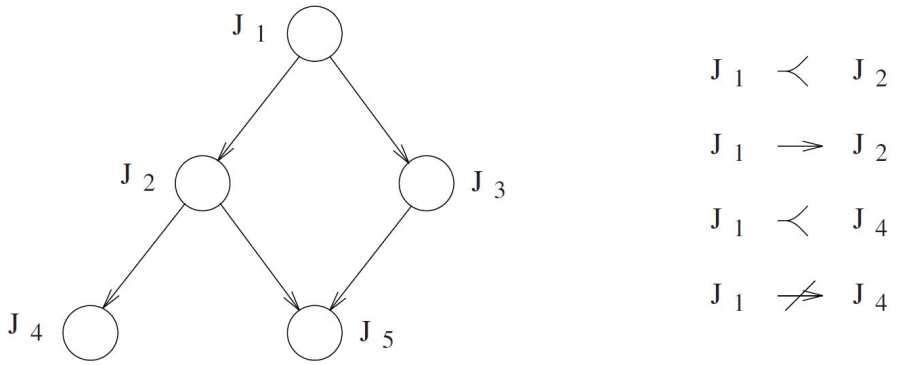


Figure 2.8: Precedence relations among five tasks [6]

In the right side of the Figure 2.8 the notation used for specifying predecessors is presented, i.e. $J_a \prec J_b$ so the Job J_a of a Task τ_a is a ***predecessor*** of a Job J_b of a Task τ_b. This notation presents a directed **path** from node J_a to node J_b. In addition, a designer can specify direct dependence as a ***immediate*** **predecessor** by using a notation $J_a \rightarrow J_b$. Meaning of this notation is that the path from node J_a to node J_b is connected by direct branch.

In conclusion to timings and precedence relations, precedence constraints can have high influence on execution of following Tasks and even to cause those Tasks not to meet its' deadlines. As it is depicted in the Figure 2.8, only J_1 is independent on start time, while J_2 and J_3 **cannot** start before the J_1 has finished its execution. Furthermore, J_5 has highest level constraints since it needs all jobs J_1, J_2 and J_3 to finish its execution before J_5 can starts its execution. The mentioned causal reaction to precedence constraints for a Task to miss its deadline is presented in the following Figure 2.9.

As it is depicted in the Figure 2.9, using red arrows, J_2 will start its execution only after a J_1 has finished its execution, although a release time of J_2 arrived before release of J_1. Now, in the given example, it is assumed that index numbers of jobs present also their priority level and lower number corresponds to higher priority level. Therefore J_2 will start its execution before J_3. After J_3 has finished its execution, since J_4 has not arrived yet, a job J_5 will start execution. On the release time of job J_4, job J_5 will be preempted. During an execution of J_4, a deadline of J_5 will be passed meaning that the job J_5 will not meet its deadline. Missing a deadline can lead to severe consequences in the system behavior.
Concluding, timing constraints as well as predecessor constraints are highly important in the design of an embedded system. In the following Section 2.2.4, different approaches to ensure the system being safe and consistent with high level of determinism will be discussed.

[3]Green bars - correct execution; Orange bar - preempted time of a task; Red bar - execution after the deadline

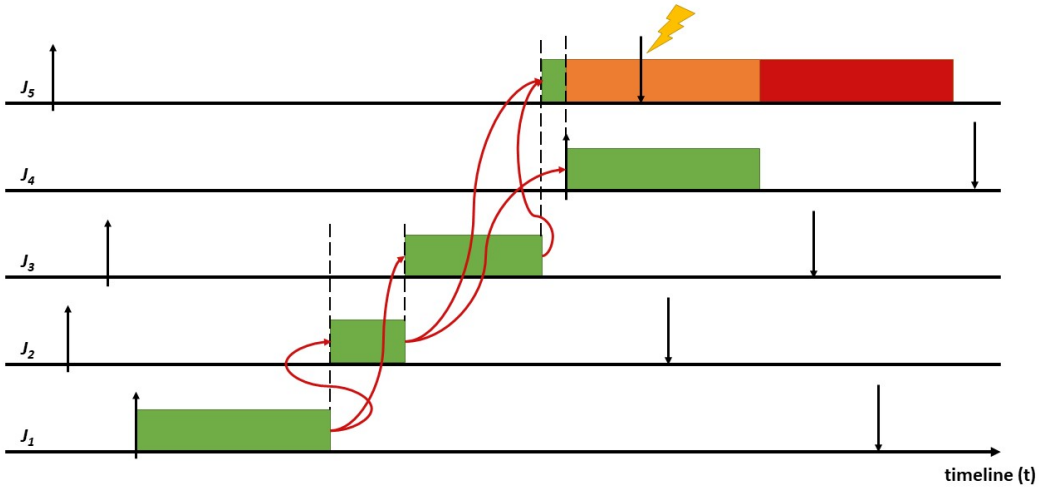


Figure 2.9: Precedence relations causing J_5 to miss the deadline[3]

2.2.3 Resource constraints of a Task in the Embedded System

When it was spoken about predecessor's constraints, the reason for a relation between two tasks are: order of execution due to system states or reading a data produced by other task or some other reason. In this section, regarding a consumption of same data by two or more tasks will be discussed. A data, or a data structure as it will be considered in the following discussion, is commonly a set of variables, a main memory area, a file, a piece of program, or a set of registers of peripheral device [6]. A data structure can be either *private*, dedicated to a particular task, or to be *shared resource*, when it is a resource that can be consumed/accessed by more than one task.

The main issue with shared resource is a data consistency which can be restricted by introducing additional measures not to allow simultaneous access, neither writing in nor reading out. If it would not be a case a following scenario could happen. Referring to Figure 2.10 [6], as an example, a task τ_D could start reading a data from a shared resource R. It would firstly read data $x = 1$, but then Task τ_W would preempt Task τ_D and write in new data: $x = 4$ and $y = 8$. When a control is given back to Task τ_D, it would read a new value written in variable $y = 8$. By that Task τ_D would have read a pair $(x, y) = (1, 8)$ which is indifferent from a original state $(x, y) = (1, 2)$ and also from a new state $(x, y) = (4, 8)$. Therefor a mutual exclusion is needed in order to prevent a task to access a shared resource R if another task is already accessing R. A shared resource R is then called a *mutual exclusive resource*. A task that has an access to the mutual exclusive resource R will need to lock a resource to prevent others from gaining an access to it too. The part of the code, between locking the resource R and releasing it, is called ***critical section***. In the previous Section 2.2.2, the *blocking time* is described. The reason for a task to be blocked is that a task with an access to the resource

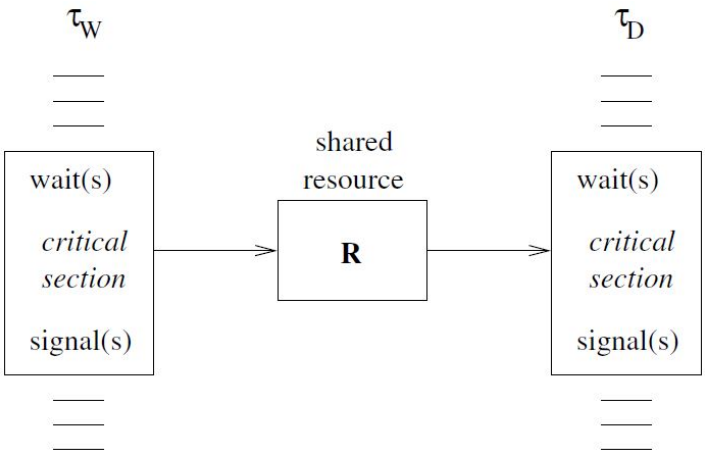


Figure 2.10: Structure of two tasks that share a mutually exclusive resource protected by a semaphore [6]

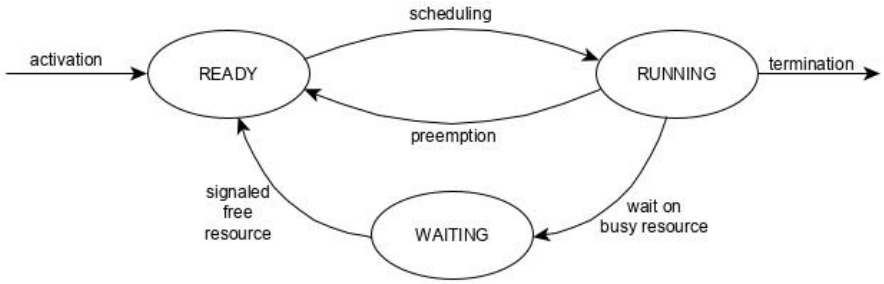


Figure 2.11: Task's state diagram [6]

R needs to wait until it is been released by other task with the access to the same resource R. Locking (*wait*() command) and releasing (*signal*() command) a shared resource from a used is provided by an operating system using a synchronous mechanism: semaphores, mutex, etc.Using one of these synchronous mechanism, a task will encapsulate the instructions that manipulate the shared resource into a critical section [6].
Defining two types of a task being stalled from an execution we can define task states and events that trigger state change. States of a task, in general [6], are: *ready*, *running* and *waiting*. States changes of a task are presented in the Figure 2.11.

Upon an initialization of a task τ_i, the release time r_i of the task τ_i will be set. When r_i is reached, the task will be inserted into the *ready* queue as being ready for the execution. The ready queue is sorted based on the priority levels. When the task τ_i is the next task in the ready queue, it will be then scheduled and moved into the *running* state. During the execution of τ_i, if a higher priority task τ_H is inserted into the ready queue, a task τ_H will preempt a task τ_i. In other words, τ_H will be moved to the *running* state, while τ_i will take a *preemption* branch and will be stored in the ready queue. After going a back into the ready state, let's assume, the task τ_i needs to access some shared resource R. Before entering a

critical section, task τ_i checks the availability of the resource. Upon checking, a task τ_i reads the resource R is blocked by some lower priority task τ_L that was preempted by a task τ_i. Therefor a task τ_i needs to free the CPU for a task τ_L to finish its process and free the shared resource R. Therefore, a task τ_i cannot be stored in the ready queue as it would mean that it will preempt τ_L and get instantly back to running state. Due to that reason, a third state *waiting* state exists. When a task just before a critical section execution reads that a shared resource R is busy, then a task τ_i will move to waiting state. As soon as the resource R is released using a signaling method, a task τ_i will be moved to ready queue. The reason for moving into the ready queue is due to the reason that during an execution of the critical section of task τ_L, some task, i.e. τ_H again, with higher priority than task τ_i has been release. After release of the resource R and a task τ_i being moved to ready queue, a high priority task τ_i will preempt now again a task τ_i. Finally a task τ_i will continue its execution after a task τ_H has finished its execution. As soon as the τ_i is back in running state, it will check again if the shared resource R is free and if it is, a task τ_i will call a method $wait()$ and lock the resource R. It will execute critical section and after finishing critical section, τ_i will call a method $signal()$ to release the resource R. Finally, when a task τ_i has been fully executed, it will be terminated. When it's next release time has been reached, a process will start over again by activating a task τ_i and moving it to the ready queue.

2.2.4 Scheduling and Resource Allocation in Embedded Systems

After defining timings and resources, a scheduling of tasks will be discussed. As it is well explained in [6], a scheduling problem can be defined, in general, using three sets:

- a set of n tasks:

  $$\Gamma = \{\tau_1, \tau_2, \ldots, \tau_n\}$$

- a set of m processors:

  $$P = \{P_1, P_2, \ldots, P_m\}$$

- a set of s types of resources:

  $$R = \{R_1, R_2, \ldots, R_s\}$$

Additionally to these sets, a precedence constraints directed acyclic graph G can be assigned as defined in the previous Section 2.2.2. Scheduling, in a broader sense, is a process of assigning processors $P_i \subset P$ and resources $R_i \subset R$ to tasks $\Gamma_i \subset \Gamma$ in order to be able to execute all tasks under system design constraints. Thus, during a design time, each task will be assigned with a certain resource elements, i.e. memory, communication channel, etc. Also, each task will be specified with timing characteristics defined in Section 2.2.2. Finally, each task will be mapped to the given processor(s) and utilization bound, specified in Section 2.2.1, will be checked whether a task set $\Gamma_i \subset \Gamma$ is schedulable on the given processor P_i.
Task set $\Gamma_i \subset \Gamma$ is said to be ***schedulable*** if there exist at least one algorithm that can

produce a *feasible* schedule. In addition, a schedule is said to be ***feasible*** if all tasks can be completed according to a set of specified constraints [6].
Scheduling algorithms vary in methods used to organize the task order of execution. Mainly, scheduling algorithms are distinguished based on [6]:

- **Preemptive vs Non-preemptive**

  Preemptive scheduling takes into the account that a lower priority task τ_L can be preempted by a higher priority task τ_H, as it was seen in the example in Figure 2.9. On the other hand, there is non-preemptive scheduling, once a task τ_i has started its execution, it will be processed until its' completion and then being terminated. By non-preemptive scheduling, a scheduling decision are taken upon an running task being terminated;

- **Static vs Dynamic**

  By static scheduling algorithm, all system parameters are fixed in the design time and cannot be changed during a runtime, i.e. priority level, timing and preceding constraints, etc. Whilst dynamic scheduling algorithms can change tasks parameters during a runtime based on certain system dynamics. For an example, Earliest Deadline First (EDF) algorithm dynamically change task's priority level, depending on their deadlines. Thus, a task, whose deadline is the closest to the point in time when a scheduling decision is being made, will have the highest priority level;

- **Offline vs Online**

  Similarly to static and dynamic scheduling, when it comes to offline and online scheduling, they differ when a scheduling decision have been defined. In offline scheduling, the schedule is generated and it is stored in a table (*scheduling table*) that is used later on during a runtime by a dispatcher. However, an online scheduling algorithm takes decisions during a runtime, every time a new task enters the system or when a running task terminates;

- **Optimal vs Heuristic**

  An optimal scheduling algorithm is called the one that minimizes some given cost function given over the task set $\Gamma_i \subset \Gamma$. Similarly, a scheduling algorithm is said to be heuristic if a heuristic function is used in taking a scheduling decisions. The main difference between optimal and heuristic scheduling algorithm is that heuristic tends toward optimal schedule, but does not guarantee that the one will be found.

When choosing a scheduling algorithm, a designer must takes into account whether a system is soft, firm or hard real-time system. Not all algorithms will achieve a feasible schedule. Now, two commonly used scheduling algorithms will be explained - **RM** as static scheduler and Earliest Deadline First (EDF) as dynamic scheduler.
Rate Monotonic Scheduling is a fixed-priority based scheduling. The RM assigns priorities to tasks according to their deadlines (periods - if $p_i = d_i$), meaning a task τ_H with

$n\backslash\delta$	0.5	0.6	0.7	0.8	0.9	1.0	2.0	3.0	4.0
2	0.944	0.928	0.898	0.828	0.783	0.729	0.666	0.590	0.500
3	0.926	0.906	0.868	0.779	0.749	0.708	0.656	0.588	0.500
4	0.917	0.894	0.853	0.756	0.733	0.698	0.651	0.586	0.500
5	0.912	0.888	0.844	0.743	0.723	0.692	0.648	0.585	0.500

Table 2.1: RM utilization bound function data

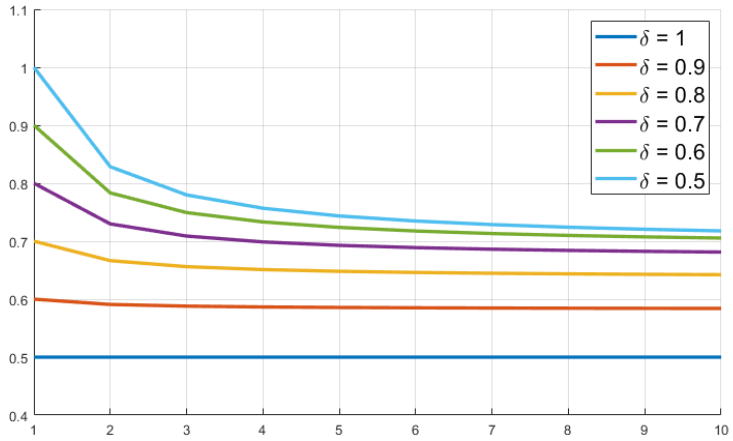


Figure 2.12: Graphical representation of the Table 2.1

a relative deadline $d_H = 10ms$ will be assigned higher priority level than a task τ_L with a relative deadline $d_L = 20ms$. Since deadlines (periods) are set during a design time and thus being fixed, therefore an assigned priority level P_i given at the design time too, will not change over time during a runtime. These characteristics influence the determinism of the scheduling and thus a scheduling algorithm in AUTOSAR is based on RM - more about AUTOSAR scheduling algorithm in the following Section 2.3.
RM scheduling guarantees feasible schedule if an utilization is less or equal than an utilization bound function, for a single processor unit [22], defined in Equation 2.2, where $d_i = \delta \cdot p_i$:

$$U(n) = \sum_{i=1}^{n} \left(\frac{e_i}{p_i}\right) \leq U_{RM}(n,\delta) = \begin{cases} \delta(n-1)\left[\left(\frac{\delta+1}{\delta}\right)^{\frac{1}{n-1}} - 1\right], \delta \geq 1 \\ n\Big((2\delta)^{\frac{1}{n}} - 1\Big) + 1 - \delta, 0.5 \leq \delta \leq 1 \\ \delta, 0 \leq \delta \leq 0.5 \end{cases} \tag{2.2}$$

Using a function presented in the Equation 2.2, we can construct a table with calculated values corresponding to n - different number of scheduling tasks and δ - different deadline/period ration. For $p_i = d_i$, utilization bound $\lim_{n\to\infty} U(n) = \sqrt{2}$

If RM utilization bound is not fulfilled, it does not necessarily mean that there is no feasible schedule, but it is only not being guaranteed. Some other scheduling algorithms, like EDF, have utilization bound $U_{EDF} = 1$ for utilization processor, as it is not being *'pessimistic'* as RM scheduling. More about EDF, can be read in [21]. EDF will not be considered here since it is not used by AUTOSAR. It is used in here only as an comparison example to RM and also as one of the commonly used online schedulig algorithms. More about scheduling and constraints in AUTOSAR will be discussed in the following Section 2.3

2.3 AUTOSAR as a Real-Time System

AUTOSAR is guided by the approach of Model Driven Development (MDD), Figure 2.13. The modularity makes the system more independent during a development phase. In addition, upgrades of separate modules are separately developed. The reason for MDD nowadays is explained in Section 2.1.1, Figure 2.1. Therefore, as explained in previous Section 2.1.1.2, different abstraction layers exist for different level of requirements and development of a single module. The main level of abstraction considered in this Thesis regards the underlining elements of the Operating System developed according to AUTOSAR Standard. In a relationship to the following Figure 2.13, the work would correlate to ECU integration level as the OS is the logical power unit of the ECU.

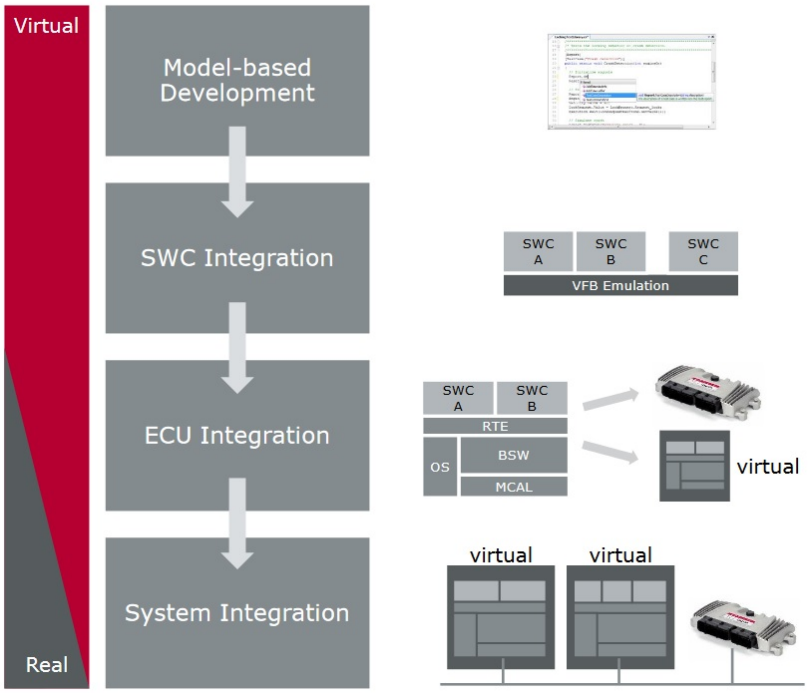


Figure 2.13: AUTOSAR Example of Top-Down development approach [7]

TIMEX
In order to ensure the constraints set by safety and security regulations, highly deterministic system with protection measures is needed. The motivation for this is given in in Section 2.1. The general discussion on Embedded Systems is given in Section 2.2. At this point, a specific elements related to AUTOSAR protection mechanisms will be discussed and presented. The AUTOSAR standard lists **three** types of online[4] system tracing for a timing verification.

- **System Hooks**
- **VFB Trace**
- **Watchdog Manager (WDM)**

Listed Instrumentation provides online verification of specifications made based on the timing analysis. General timing analysis have been discussed in Section 2.2.2, while AUTOSAR specifies standard on timing analysis through a specification document called Timing Extensions (TIMEX) [8] and Recommended methods for Timing Analysis within AUTOSAR Development [23].
Firstly, a TIMEX definition in AUTOSAR terms and an overview of TIMEX [8] will be covered, followed by some use cases presented in [23]. Important remark is the TIMEX is only specification and template for designing a system using an AUTOSAR and there is no requirements for TIMEX implementation. In running system, timing requirements are checked using system traces, as mentioned: *System Hooks*, *VFB Trace* and *Watchdog manager*. Finally, recorded traces can be tracked and analysed with additional tools. General overview of these elements will be covered in this chapter as fundamentals for designing *AutoSec* in following Chapter 3 - *System Model* and Chapter 4 - *Design Concept*.

2.3.1 Timing Extensions Overview

Overview of Timing Extensions for AUTOSAR is based on [23]. As it is depicted in the *Specification of Timing Extensions* AUTOSAR Document, the TIMEX provide some basic means to describe and specify timing information:

- timing descriptions - expressed by ***events*** and ***event chains***
- timing constraints - imposed on these events and event chains

The purpose of TIMEX is dual, to provide:

- timing requirements - guide the design of a system to satisfy given timing requirements
- sufficient timing information - to analyze and validate the *temporal* behavior of a system

Events - "*Locations in the systems at which the occurrences of events are observed.*"

[4]online - the action during a run-time

Observable locations are set of predefined event types. TIMEX differs *timing views* that correspond to one of the AUTOSAR views:

- *VFB Timing* and Virtual Functional Bus View
- *SWC Timing* and Software Components View
- *System Timing* and System View
- *BSW Module Timing* and Basic Software Module View
- *ECU Timing* and ECU Timing

Event Chains - "*Causal relationship between events and their temporal occurrences.*"

A designer is able to specify the relationship between events, similarly to precedence constraints discussed in Section 2.2.2. For an example, the event B can occur if and only if the event A has priory occurred.

- *stimulus* - considering a last given example, in a context of event chains, it is said that the event A is **stimulus**
- *response* - in addition, when event reacts on the stimulus, as the event B reacts to the event A in discussed example, then the event B is called **response**
- *event chain segments* - In addition to stimulus and response, event chains can be composed of shorter event chains called **event chain segment**.

In order to understand abstraction level of listed Views for Events, a short discussion on each will be discussed.
SystemTiming will not be considered here since it will not be discussed further in this Thesis; for more refer to [8]. On **VfbTiming** logical level a special view for timing specifications can be applied for a system or a sub-system. At this view, (physical) sensors and actuators are considered and their end-to-end timing constraints. At this view level, constraints do not consider to which system context are SWC are mapped to/implemented on. As it is depicted on Figure 2.14. VFB only refers to *SwComponentTypes*, *PortPrototypes* and their connections but not the *InternalBehavior* [23]. Thus, at VFB View level, only timing constraints from *in* to *out* from the SWC is considered. As an example, from the point in time, when the value is received *in* by a SWC until the point in time, when the newly calculated value by the SWC is sent (*out*), there shall not be a latency greater than 2 ms. The VFB View level does not take an internal construction of the SWC into the account. The lowest granularity level is Atomic SWC.

However, if we are interested in lower granularity level, it is needed to consider next Timing view - **SwcTiming**. Before explaning SwcTiming, the AUTOSAR element ***ExecutableEntity*** will be defined as an abstract class and *RunnableEntity* and *BswModuleEntityt* are specilization of this class [23]. These classes are defined in AUTOSAR_TPS_TimingExtensions - [23].

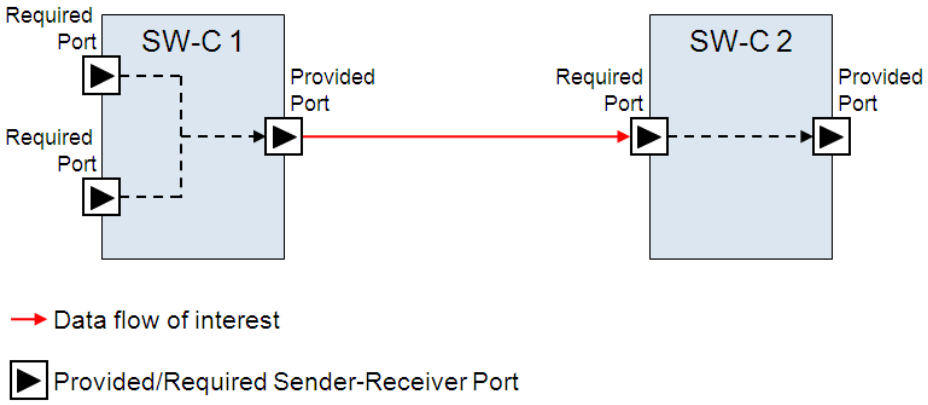


Figure 2.14: AUTOSAR Example of Data floww in the scope of the VfbTiming view [8]

At this level, a SWC is decomposed into runnable entities, which are executed at runtime. Thus, at SWC View level timings related to internal components of a SWC are considered: activation, start and termination of execution of Runnable Entities [8]. As it is depicted in the Figure 2.15, at this SWC View level, we are interested in timing behaviors of RE_1 and RE_2.

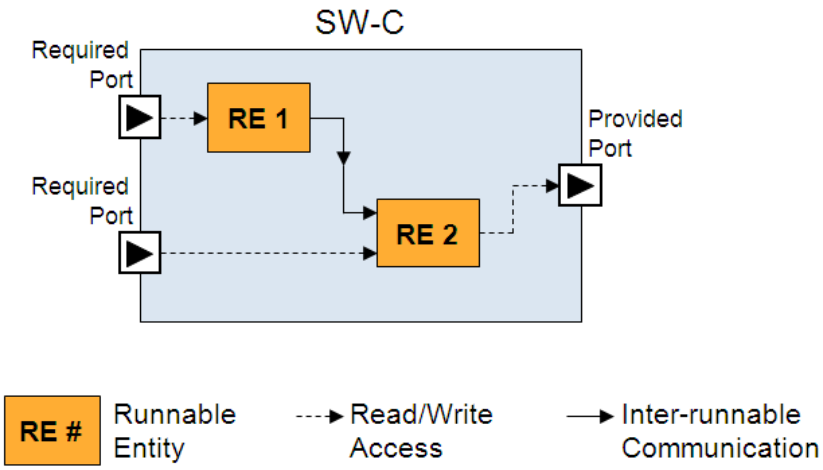


Figure 2.15: AUTOSAR Example of Data floww in the scope of the SwcTiming view [8]

In addition to Runnables, a Basic Software modules are also subject to timing constraints. BSW modules are considered at *BswModuleTiming*. As defined in [TPS_TIMEX_00035] in [8] - Purpose of BswModuleTiming: *The element BswModuleTiming aggregates all timing information, timing descriptions and timing constraints, that is related to the Basic Software Module View, referring to [RS_TIMEX_00001].*

The main goal of TIMEX Specifications are described by [RS_TIMEX_00001] from [8]:

- Description: The AUTOSAR templates **shall provide** the means **to describe the timing properties of a system's dynamics**, which are determined by the consumption of computation, communication, and other hardware resources.
- Rationale: The description of timing properties in the AUTOSAR templates is an **essential prerequisite** for the analysis and validation of a system's timing behavior or its prediction early in the process.

However, regarding specifications by OEMs, timing constraints are usually only specified for a limited number of tasks, commonly for safe-related sub-systems, but not for the complete system. For tracing a timing requirements specified during the design time in the AUTOSAR, a few methods are used. As it was listed at the beginning of this section, those methods are: System Hooks, VFB Trace and Watchdog Manager. Using these elements depends on the implementation of the standard and thus there will be no detail explanations on them. VFB is related on tracing communication between Software components, while System Hooks are related to more BSW modules and Watchdog is used to clarify that hard boundaries of the operating system are not overstepped. More about functionalities and more indetailed descriptions and explanations are provided by the AUTOSAR's implementation of interest.
In the following Chapter, the discussion will be led on the IDS methods as the research part on the motive of the Thesis work.

Chapter 3

Related Work

Before speaking about the Prior-Work done as part of the research to come up with *AutoSec* (AUTOSAR Security) as proposed method later in the Thesis, a few words about the general items on Cyber-Security are to be said. Mainly, Cyber-Security topic and field is rapidly expanding field of research and defense, earning high points on top priorities while bringing close to none value to the market. Meaning behind the security is that customer is expecting it and it is not willing to pay extra money for security nor safety features. Thus, Cyber-Security is hard field to work in, especially considering that potential attacks are commonly not known in advance, before those happen for the very first time somewhere in the World. But, if an engineer knows the field and application of interest, then a potential level of threats decreases in some amount. As an example, there is a difference between protecting a Windows PC or Linux PC or MAC PC, or protecting the WiFi router and communications going through it. Therefore, there are different types of protections and different ways of detecting an attack. If a set of attacks ([24] and [25]) is known in advance, then a prior detection and protection methods can be installed. But what happens if a new unknown attack is performed? More about this topic in upcoming Section.

3.1 Cyber-Security

3.1.1 Network-based

For the work of the Thesis, only topics related to Embedded Systems will be taken into the consideration. Nonetheless, Intrusion Detection Systems are generally divided into two main groups called: Network-based Intrusion Detection System (NIDS) and Host-based Intrusion Detection System (HIDS), as depicted in the Figure 3.1.

Network-based IDS is oriented towards intrusion detection on network / communication medium level. The topic of NIDS evaluates and develops algorithms related to:

- Monitoring and Analyzing NETWORK traffic (i.e. on communication medium)
- Inspecting packets (i.e. packet signature, credentials, etc.) by checking Network Rules

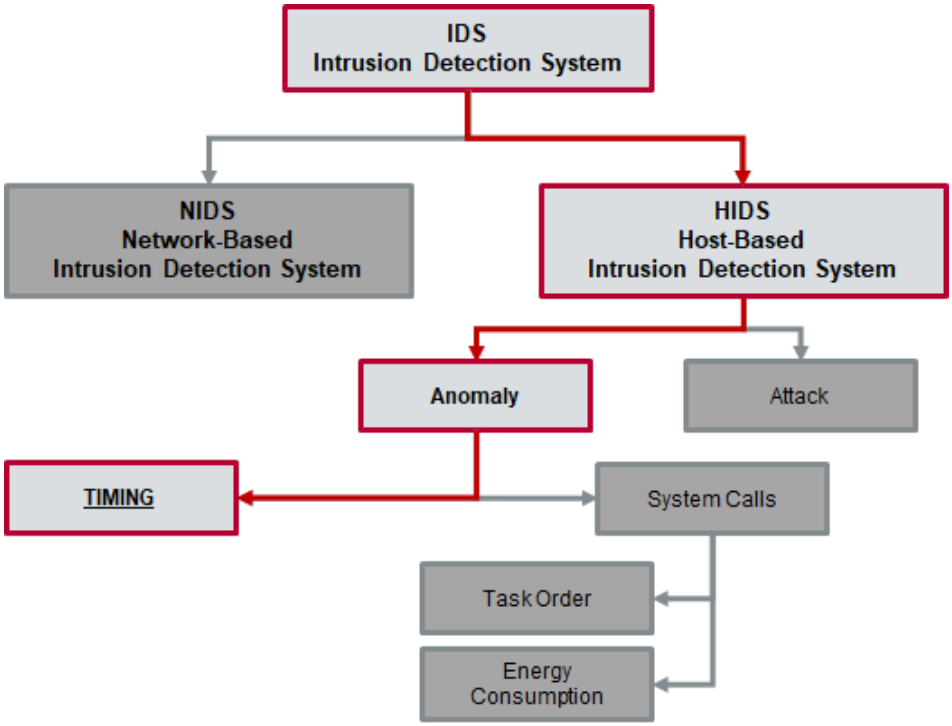


Figure 3.1: Different approaches on Intrusion Detection Systems

The topic of NIDS in AUTOSAR is covered by PhD Thesis [26]. The contribution from [26] are in terms of fast evaluation on signal level of CAN communication in the car and detecting anomalistic values coming in. The algorithm proposed by [26] evaluates multiple solutions based on Machine Learning techniques, where the Autoencoder technique resulted in the best outcome and performance level. Further elements on how Autoencoder works are not in high interest of this Work and for further details it can be read more in [26]. The outcome of the best result is:

- $FalsePositiveRate(FPR) = 0 - 0.0072\%$
- $Recall = 86.2 - 89.2\%$

The meaning of these elements (FPR and Recall) can be read in Chapter 6 - Section 6.1. False Positive Rate and Recall are evaluation measures used in Machine Learning to measure success and how good is the system. False Positive Rate reflects how many false alarms have been raised by the system and Recall represents how many actual anomalies/misbehaviors/-malicious work/attacks have been successfully detected.
Since NIDS is the field widely been researched, mainly in Communication Engineering, over past few decades and these methods in majority of cases can been implemented in the AUTOSAR and Embedded Systems with no or minor adaptations, the main scope of the Thesis is towards HIDS.

3.2 Host-based Intrusion Detection System

In comparison to Network and communication oriented algorithms, HIDS methods focus on a host of the running programme or application. Thus, the algorithm focus on internal behavior of the system, such as: HIDS algorithm runs indepenendly on each individual host separatelly. HIDS checks on internal consistency and workflow used on critical machines, i.e. unexpected change in the configuration, unfulfilled any of predefined rules within the system, etc. According to approach used to detect an attack, HIDS can further be divided as depicted in Figure 3.1. Similarly to NIDS, a detection system can be based on already known attack(s), or on detecting anomalies in system behavior as a consequence of an unknown attack.
Since, in Embedded Systems and modern AUTOSAR based architecture, close to none attacks, best to the authors knowledge, are known. The most known attack was executed as a scientific experiment in controlled environment by two scientist - Charlie Miller and Chris Valasek [2]. They have gained an access to Jeep Cherokee vehicle through wireless network and were able to manipulate the car functionalities:

- Dashboard control
- Engine Control
- Brakes Control
- Steering Wheel Control
- Radio and Volume Control
- GPS signal tempering
- Chassis control (locks, wipers, horn, etc.)

The attack itself could be classified as an attack on a specific type of vehicles with a loophole in the vehicle system architecture having an exposure to external malicious control. Nevertheless, the outcome of such attack had enormous impact on the automotive industry, since scientists Miller and Valasek were not only able to manipulate communication channels, but also to change the program running on ECUs in the car and thus completely overriding the program and functionalities installed by the manufacturer.
Thus, in order to be prepared for such extraordinary exposures to outside world, the possibility was to look for anomalies in system behavior during runtime in order to have an early detection of such breaches. Followed by this direction of industry thinking and development learned by the example of [2] outcomes, decision has been made to follow Anomaly detection as a base method of HIDS.
The method in use will be based on Software implemented algorithms and Hardware-based methods would not be considered in this work. The reason to do so is based on fact that the Software can be used by minor changes on different hardware architectures of ECUs and thus brings higher value to the industry by reducing the (re-)design time and easier implementation, by avoiding overhead in space and production time introduced by hardware-based

algorithms (i.e. algorithms on FPGA).
When it comes to hardware, some algorithms used a Micro Control Unit (MCU) in-built feature of measuring the energy consumption of the MCU/CPU. The energy consumption is monitor and its profile is recorded. The anomaly in the system behavior is detected if the energy used by MCU/CPU deviate from the recorded profile. The downside, not all MCUs (since CPUs are not used in CPU) poses highly precise and fast enough energy consumption meter to reach low enough number of False Alarms. Contrary to Hardware features support, some algorithms monitor the order of functions execution, as it will be discussed in the following Section 3.2.1.

3.2.1 System Calls

Following the tree from the Figure 3.1, next step is to do a research on anomaly detection algorithms being proposed by literature. Scientific papers showed that the most occasional approach is based on the System Calls (SysCall) technique, such as [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37]. The System Call algorithms learn and monitor the program execution flow and order of system calls within. System Call algorithms previously cited papers focus on following mathematical models:

- Merged Decision Tree
- Probabilistic Suffix Tree
- k^{th} Markov Chain
- Probabilistic Determination
- others statistical methods

Since System Calls have one common disadvantage pointed out by [36]:

"“. . . since execution traces follow the program flow, if executions diverge at a certain point, it is common that they lead to distinct execution paths from then on.".

Thus, System Calls as is not a field of an interest as an HIDS method to be used in automotive industry since this can lead to sudden high level of False Alarms that could be resolved by restarting system and starting the program execution from the beginning.
By evaluating results, the premises is confirmed by test evaluations that False Alarms (FPR) tend to be high for automotive industry. In a case of a function, which is being executed every 10ms, happens that FPR is 0.1%, the outcome is that every 1000^{th} execution of the function will report an anomaly. In other words, 1000^{th} function is every 10 seconds, thus, false alarm will be raised once in every 10 seconds for one single function that is monitored. From papers cited throughout this section, vast number of them have been giving only a method proposal without showing results in number from *Evaluation* phase. The results of evaluation have

	FPR	Recall	Precision
System Call Distributio[27] - Threshold 1	0.22792%	*N.A.*	*N.A.*
System Call Distributio[27] - Threshold 2	0.05698%	*N.A.*	*N.A.*
LogSed[33]	1.125%	82.5%	78.5%
Machine Learning on SystemCalls[28]	8.80%	100%	40.05%

Table 3.1: Results of System Calls algorithm on *FPR*, *Recall* and *Precision*

been discussed only in terms of capabilities detecting an anomaly. The evaluations are written as a discussion on parameters of *AutoSec* and its general influence on the results. Papers that have provided the numbers of results, are displayed in the following table.

Conclusion is, some other approach shall be considered for HIDS algorithm used in automotive industry. The next approach is to use timing features to detect anomalies in system behavior. In this Thesis, it is called Time-based Anomaly Detection.

3.2.2 Time-based Anomaly Detection

Time-based Anomaly Detection is used as a name, in this Thesis, for algorithms that are based on timing features explained in details in Figure 4.1. In Embedded Systems, some timing features have certain thresholds as an indicator of some misbehavior in the system. The example is monitored execution time of a Task. The time is monitored by watchdog timer [38]. If the watchdog timer runs out, in AUTOSAR a *ErrorHook* is triggered and a handler is called to mitigate the error in the system. The timing used to set watchdog timer is rather long with a margin over WCET. Thus, if a watchdog timer runs out, the meaning is that the function currently active stalled and blocked whole MCU as a resource from other functions. Therefore, such method cannot be used for detecting anomalistic behavior.
However, using similar idea, a method has been proposed by [9] - called ***SecureCore***. Yoon

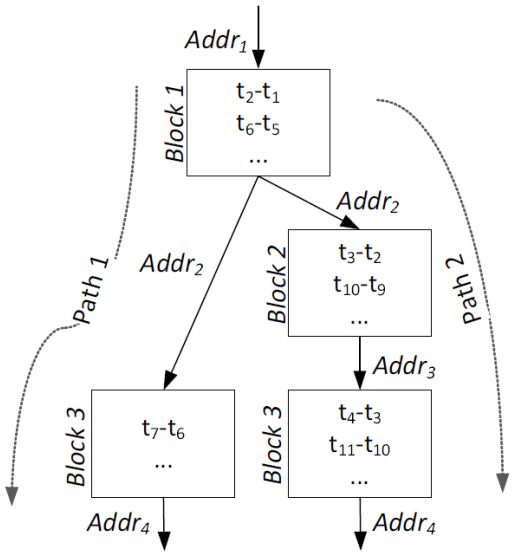


Figure 3.2: [9] - Trace tree generated from a sequence of traces

et al. have measured function execution times and generated the probality density function (*pdf*) of execution time measured on a single function. The *pdf*is generated by running the measurements over the same function multiple times (Figure 3.2), and the distribution of its timings is calculated. The result is presented in the Figure 3.3.

SecureCore method by [9] proposes to generate probability distribution of execution time, and set a threshold on minimum probability value. Thus, during a runtime, a new execution value will be calculated and checked whether that execution value falls in the Gaussian distribution over minimum requested probability - above red line in the Figure 3.3. Now, the question arises, whether the value between two Gaussian distributions in the Figure 3.3 that would be considered as an anomaly, is it a real anomaly? The evaluation results in [9] showed following results:

- Higher Threshold
  - FPR = 0.098%
  - $Recall = 45.12\%$
  - $Precission = 99.89\%$
- Lower Threshold
  - FPR = 0.6897%
  - $Recall = 88.43\%$
  - $Precission = 98.54\%$

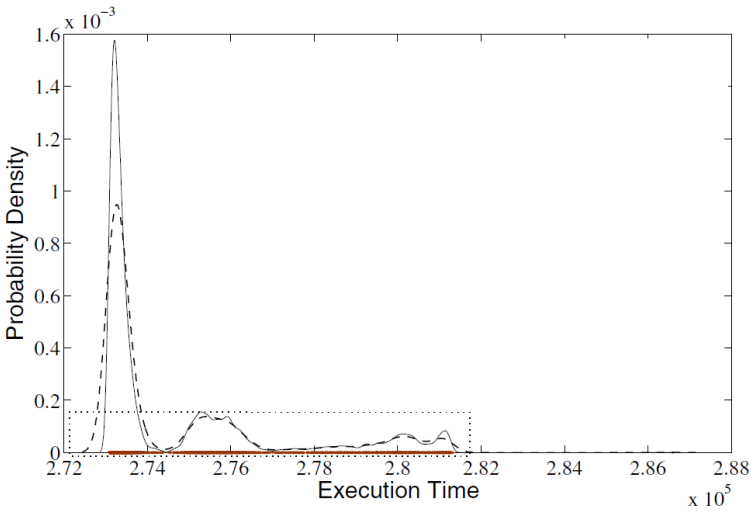


Figure 3.3: [9] - Probability density estimation of an example execution block

The results show that the low probability of some execution times influence highly ratio between FPR and Recall since for higher thresholds a Recall was below 50%, while for lower threshold FPR was too high for automotive industry (0.6897%). An answer to the question whether low probability execution times could be really considered as anomalies will be discussed in the following example. Tracing is done similarly as in [9]. More about tracing and implementations in the following Chapter. Probability density functions are generated for computation time, as well as for S2S times. Then, these two density functions are overlapped and two dimensional scatter plot is generated, as upper-right plot in Figure 3.4.
Computation time around $212\mu s$ falls between two Gaussian distributions in *pdf* of Computation time and thus according to [9] shall be considered as anomaly. However, taking a look into the upper-right plot of Figure 3.4, data points with this long computation time, had S2S time equal to $10.05ms$ and not falling apart from other data points in 2D space. Contrary to that, a single data point (lower red round) is far from the rest and thus being an outlier that could be considered as the anomaly. However, it's computation time is in range between $205 - 210\mu s$ and by [9] it would be considered as a normal behavior. Due to such examples, the proposed method [9] resulted in high level of False Alarms that needs to be reduced in order to be applicable in automotive industry. Hence, the objective of the Thesis is to increase reduce the number of False Alarms (FPR) while maximizing the Recall. Hence, the novel Host-based Intrusion Detection method for Real-Time automotive systems, called ***AutoSec***, is proposed by the Thesis. More about ***AutoSec*** will be discussed and explained in the following Chapters.

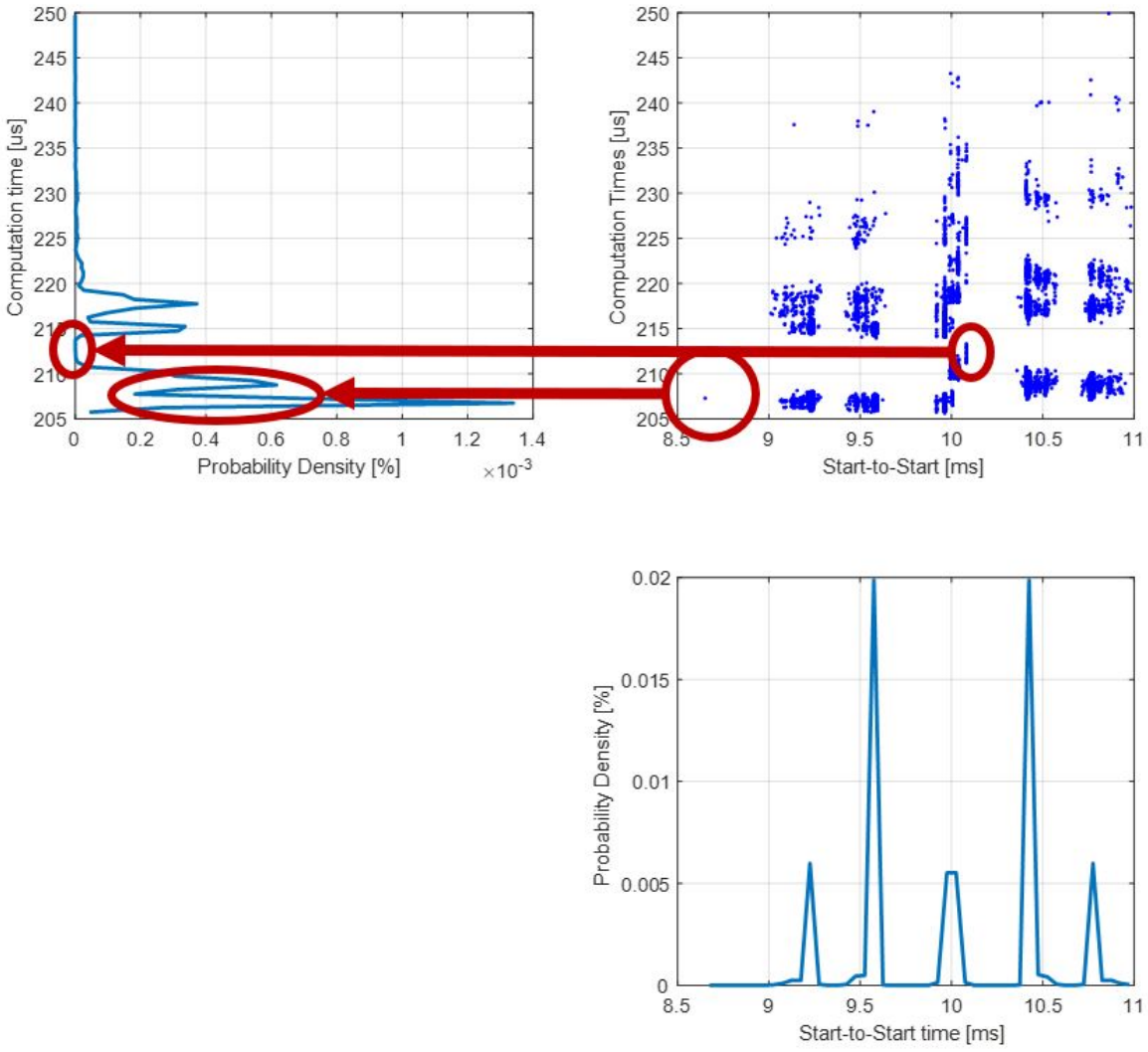


Figure 3.4: Probability density function on two dimensional random variable $X(S2S, computation)$

Chapter 4

Concept and Design

4.1 Timings' Features

By reading papers and literature presented in the previous Chapter 3 about methods used for Intrusion Detection, a new concept can be developed in order to detect anomalies during an execution of the embedded system code. According to the research conducted throughout this Master thesis, there was no much work and papers about IDS based on timings in embedded systems. Depicted in Figure 4.1 from Section 2.2.2, apart from the execution time only, there are more timings that could be tracked. The contribution of this thesis is a conducted research about the relevance of other timings in the system and how those values can be exploited. Due to the limited time to endeavor the Thesis, the authors have opted for four timing feature to be used as anomaly markers. The chosen features in this novel approach, best to the authors knowledge, are: total computation time, start-to-start time, number of preemptions during an execution of a job of the task, and the total duration of those preemptions. More about each of these features will be presented in following sections.

Before coming to each feature separately, a reasoning about the choice of features will be given first. Examining Figure 4.2, it can be seen how Jobs/Runnables of higher priority task can preempt so often a lower priority task. In addition to higher priority task, preemption can be triggered externally by new messages arriving on a communication channel. These preemptions of preempted task can push start of the next Runnable in that task. This is the reason why start-to-start is one of the features that can detect anomalies. Therefor, too many preemptions would mean that there is some additional execution that is not there in *normal* execution. In addition, too long preemptions could mean that a higher priority task has been preempted with some sudden execution of even higher priority task that *normally* does not execute at that time. Finally, the last feature is computation time that reflects the designed computation time needed to process the data in *normal* circumstances. How these values deviate over time and how are they interconnected, will be discussed throughout each separate subsection for each feature itself.

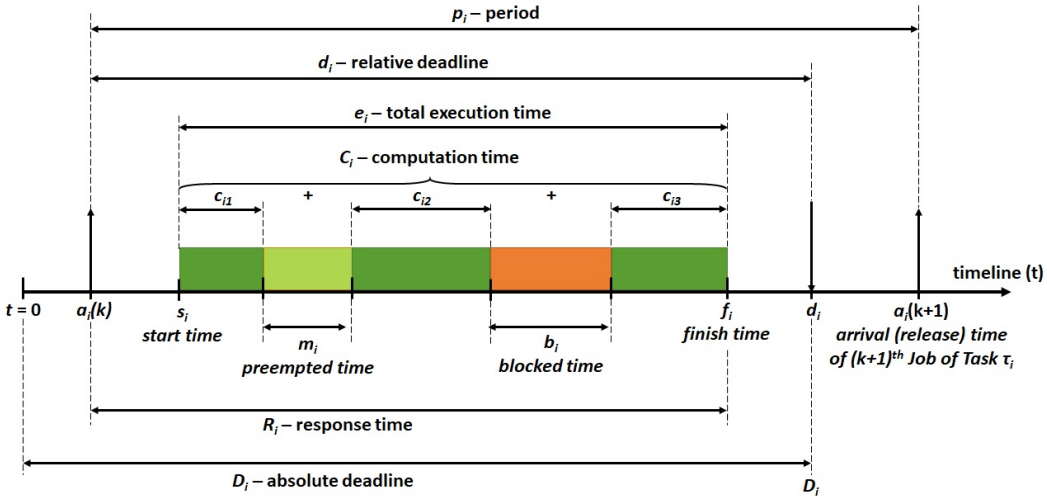


Figure 4.1: Typical timing parameters of a Real-Time Task τ_i - previously explained in Section 2.2.2

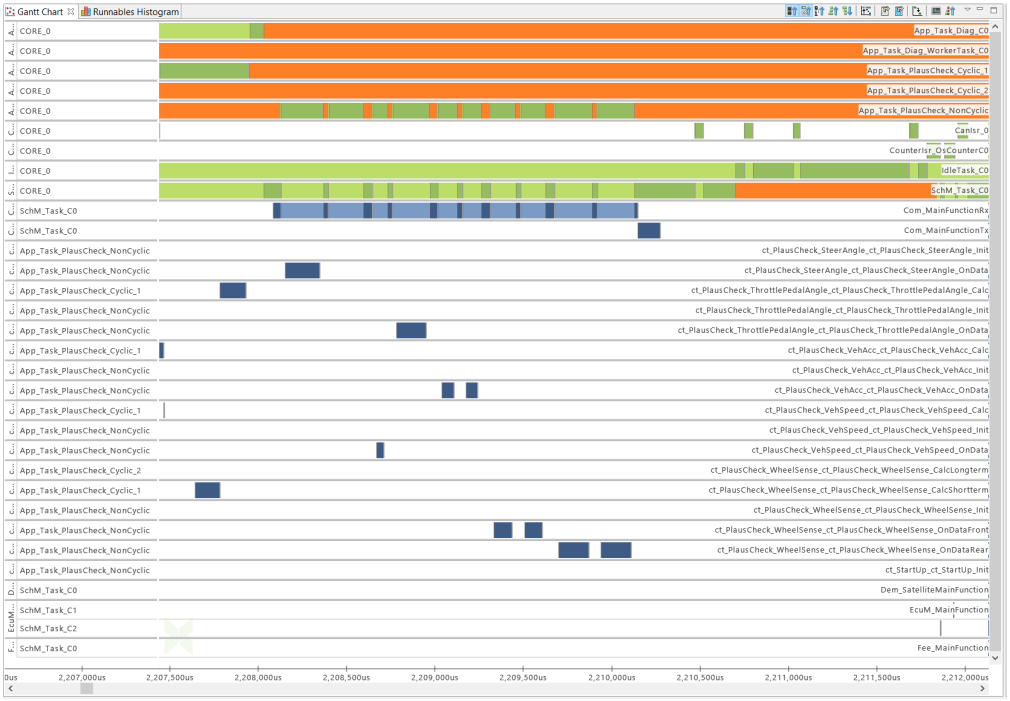


Figure 4.2: Example of Execution Diagram using TA Tool Suite [10]

4.1.1 Computation time (Execution time)

First of all, a computation time would be the most reasonable feature as it was already discussed in Section 3.2.2 - *Time-based Anomaly Detection* how computation time can be used for detecting anomalies and what is the overhead of a such approach. However, in this thesis, the algorithm goes a step further, interconnecting the computation time value with other timing features. The main reason is that some anomalies cannot be detected using a computation time only.
Firstly, computation time varies due to many reasons. The main reason is the data size that needs to be processed. As an example, it is easier to calculate integer values from CAN message rather than float values. Furthermore, if in the Runnable function we have some *for/while* loops and multiple *If* statements, this brings further dependencies that influence the computation time. Since embedded systems, in automotive industry mainly, is highly deterministic, we can present computation time with one or more combined Gaussian distributions. This approach was used in [9]. The question raises here: How can we make a hard-line threshold in here? What happens if the Job/Runnable has been preempted? How these preemptions influence the computation times due to context switching of the program/code in the CPU? Due to this, we need other timing features to increase the certainty if something is an anomaly or not.
The automotive industry is highly demanding industry with high level of standards - *Automotive Grade*. The main reason is passangers' safety and security followed by their comfort, pleasure, leisure and entertainment. Today, we have passed beyond simple transport utility that moves us from point A to point B. Due to these modern circumstances, automotive grade sets high standards for technology that passes the bar. Thus, speaking about False Positive Alarms - we do not want to annoy the driver with warning messages, nor to scare with messages like *Security breach*, using our algorithm. The level of False Positives that finds to be acceptable is 1 False Alarm once a year, recommended once in three years. More about these values can be read in [26]. Consequently, an objective function to rate the algorithm is to maximize the True Positive Rate while keeping the False Positive Rate close or equal to zero. More about these values will be discussed and presented in Chapter 6 - Evaluation.
Before coming to evaluations and testing of the algorithm, other features will be discussed. The next one talks about the Start-to-Start time.

4.1.2 Start-to-Start

When it comes to S2S time, this feature helps to detect if some other Task / Job / Runnable was running and pushing the start time of the current one (not necessarily tempered) later in time. Mainly, this timing is closely related to response time of a Task / Job / Runnable. With S2S timing feature, we can encapsulate also the knowledge whether a Task / Job / Runnable skipped its execution when it was "planned" (scheduled) or even executed more often than it was supposed to do so.
An example why Start-to-Start time as a feature is very important will be presented throughout a quick example. In case that an attacker gained an access to the ECU, and the topic of

the Thesis is not about how the access can be obtained but rather to detect the presence of 3rd parties, with a goal to shut down a certain feature in the car that is supposed to be running. As soon as the feature has been stopped from execution, another Task/Job/Runnable with lower priority in Ready queue will take place and start it's execution earlier than usual. Shorter S2S of that Runnable will raise a flag of some anomalistic execution in the ECU. Therefore, S2S flag does not necessarily points that anomaly has taken place in the Task/Job/Runnable that it is related to, but also anomaly could take place in (closely) related "surrounding" Tasks/Jobs/Runnables.
Due to this capability of S2S, it was taken to be one of the main features in *AutoSec*. Similarly, regarding Preemptions, tempering from the outside can be detected. This will be discussed in the following Section.

4.1.3 Number of Preemptions

The next feature is Number of Preemptions *($N_{preemptions}$)*. The importance of this feature lays in the ground of detected unexpected additional executions, such as Interrupt Service Routine (ISR) functions that are dependent on incoming messages from communication channels. Moreover this feature $N_{preemptions}$ detects higher priority Task(s) that are not usually scheduled to be there. An example of such case is message flooding attack that an attacker sends messages with certain requests or "spams" the ECU with random messages. This will trigger, i.e. CAN_ISR function, to process new messages. Constant interrupts from ISR will preempt a currently running Task more than it is usually preempted and the algorithm will raise a flag about anomalistic execution of the ECU.

4.1.4 Total duration of Preemptions

Contrary to message flooding, the attacker can perform more thoughtful attack by performing only a single message request with message ID, message type or destination ID with non existing values making an ECU to run extensive calculation in order to process message that has no grounds how to be processed. This type of the attack will perform only one single preemptions but it's duration will take longer than usual preemptions that take place in the system during the execution of currently being running Task. Due to this type of behavior, the last feature that will be used through this Master Thesis is the duration of all preemptions during an execution of the instance that is being traced. Total duration of Preemptions will be noted as $\tau_{preemptions}$ from now on.

4.2 Multidimensional Spaces

By defining these 4 features, we can start evaluating different feature spaces, whether the algorithm will evaluate all 4 features all together or evaluate specific combinations of these features, such as: execution time vs S2S, or S2S vs $N_{preemptions}$ vs $\tau_{preemptions}$, etc. Before

leading a discussion on evaluations of one feature space dimension(s) over the others, it is needed to remark the small preprocessing of the data points. The dataset is firstly normalized and then scaled down by 50% while keeping a center at $x = 0.5$ and $y = 0.5$ of the feature space. Thus, the scaled dataset is now in boundaries $[0.25 - 0.75]$ with the margin around it as to handle the possibility of new data points exceeding min-max values detected inside the training data set. Normalization and scale down of points will be used in any case of feature space combinations.
More about these features spaces, there will be discussion in upcoming subsections: 2D feature spaces, 3D feature spaces and single 4D feature space.

4.2.1 2D timing feature spaces

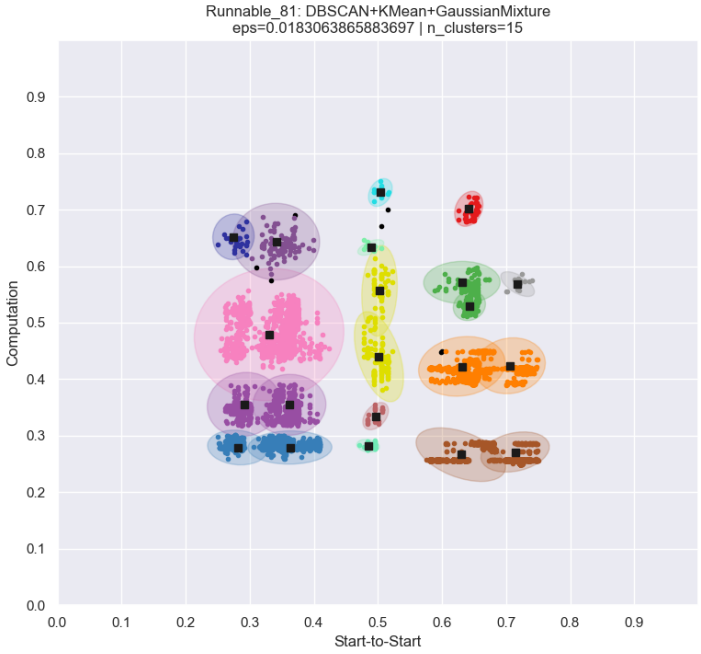


Figure 4.3: Example of 2D feature space: S2S vs. Computation time

First feature space that comes under the consideration is 2D feature space. One of the examples, used in the early stage of the development of the Thesis is depicted in the Figure 4.3. In the figure, the distribution of dataset points in the 2D feature space of S2S vs. computation time is shown. It can be noticed that data points form groupings that can be separated as clusters. Coloring is not much of an importance at the this stage of evaluations, but a quick legend on colors and points will be given.
Different colors present different clusters detected. Points that belong to corresponding cluster are colored with the same color as the boundary of the cluster. Square black points represent

the center point of the cluster while dot (round) black points represent points that could not be classified into any of clusters - it's reflected as noise in the training data set and it will be disregarded. More about this will be discussed and explained in the Section 4.3.7.
When it comes to 2D feature spaces, there are 6 combinations that would need to be examined at the end. The combinations are:

- Computation time vs. S2S
- Computation time vs. $N_{preemptions}$
- Computation time vs. $\tau_{preemptions}$
- S2S vs. $N_{preemptions}$
- S2S vs. $\tau_{preemptions}$
- $N_{preemptions}$ vs. $\tau_{preemptions}$

The correlation between each of combinations is not explicitly taken under the consideration. The focus of research reports to answer how data set for different feature spaces looks like, as well as, whether specific factors and characteristics exist so the separation line between the space with correct behavior data points and anomalies can be drawn.
Evaluating the Figure 4.3, data points have groupings that can be used for defining the space of correct behaviour of the system when it comes to Computation times and S2S. On the other hand, evaluating following Figure 4.4, not clean conclusion can be reached since the computation time can vary widely in comparison to number of preemptions

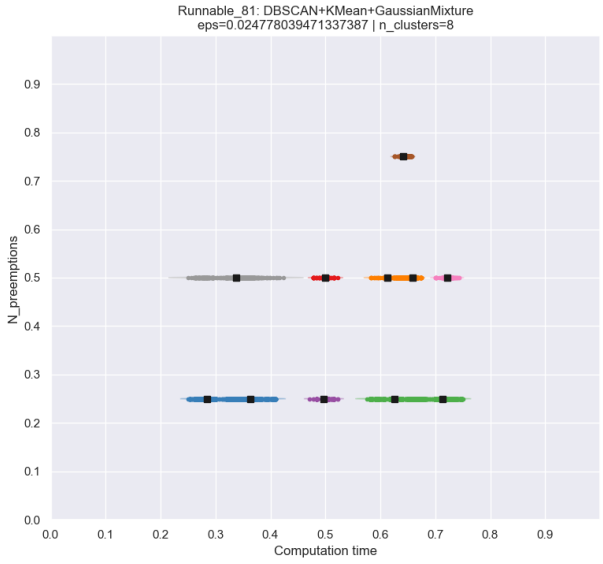


Figure 4.4: Example of 2D feature space: Computation time vs. $N_{preemptions}$

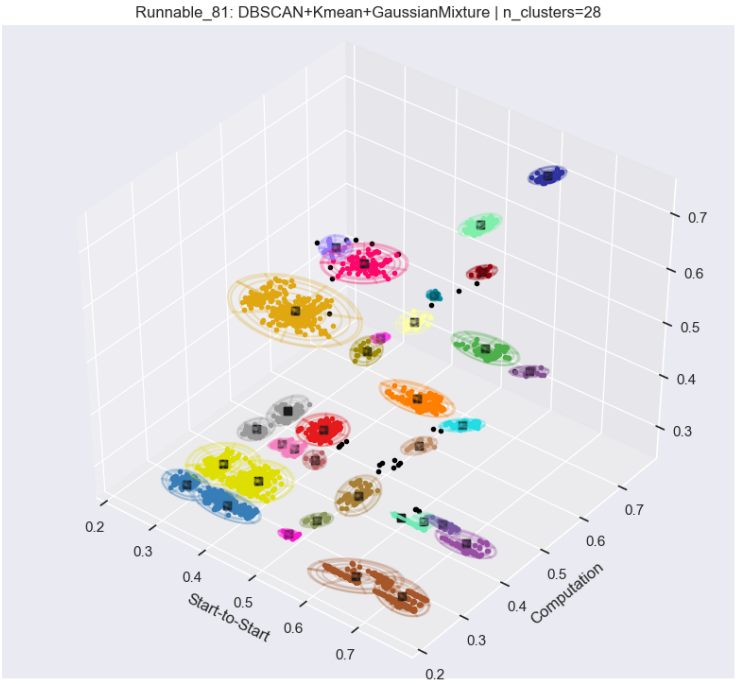


Figure 4.5: Example of 3D feature space: S2S vs. Computation time vs. $N_{preemptions}$

4.2.2 3D timing feature spaces

After seeing a potential low data separation cases as in Figure 4.4, next step is to evaluate if adding a third feature could be providing a valued information to provide more conclusive separation of groupings as space of normal behavior. The results are depicted in following Figure 4.5. Examining a show figure, it is definite that there is greater separation among data points. The separation does not necessarily bring valuable distinction. The example of such case is given in Figure 4.5. Data set has greater distribution providing new additional clusters (in total 28), in comparison 15 and 8 clusters as in Figure 4.3 and Figure 4.4, respectively. In case of the presented 3D feature space, clusters are narrowly close, so, ultimately, some clusters could be merged. More about merges will be under discussion in following Section 4.3 - Clustering Methods.
The conclusion which clustering model should have been used will not be drawn at this point but in the Section 4.4 - Clustering Results.

4.2.3 4D timing feature spaces

Before reaching the decision which kind of feature spaces and which combination of features will be used, it is needed to evaluate all features put together, meaning creating a single 4D feature space. However, a visual representation of 4D feature space is not possible. The evaluation of data set distribution and grouping for such combination of features needs to be done in mathematical evaluation rather than by graphical evaluation.
In order to draw better comparison between 2D, 3D and 4D feature spaces, a PCA will be used as a dimension reduction method. The outcome of PCA over 4D feature spaces provides a new 3D feature space. The advantages are that PCA reduces the feature space dimension in direction of correlated elements. Thus we can obtain a new feature space with filtered correlation among the elements and provided only important information embedded in the data set. Finally, newly obtained 3D feature space is possible to present graphically for further manual analysis. The result of described process is depicted in the Figure 4.6.

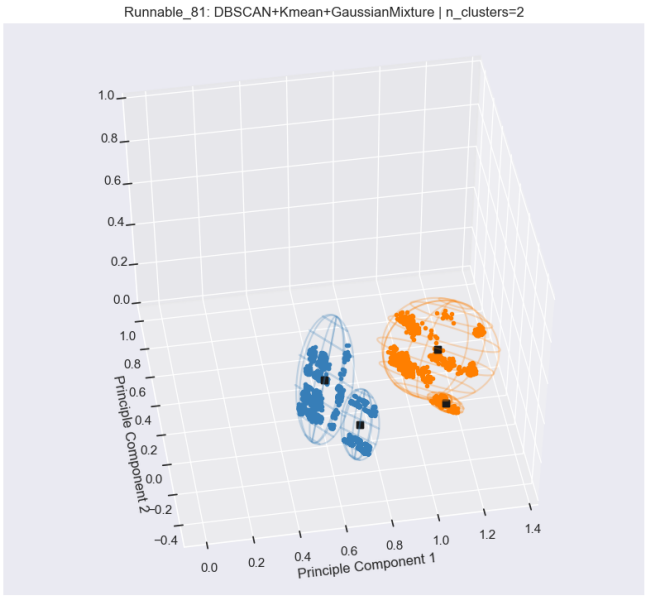


Figure 4.6: Example of 4D feature space after PCA: S2S vs. Computation time vs. $N_{preemptions}$ vs $\tau_{preemptions}$

The result shows the groupings of data points is nicely separably favoring clustering methods as the description model for the space of normal behavior of the system. Before reaching the decision, it will be discussed about which clustering methods should be used in *AutoSec*. The proposed approach of clustering can be verified using a Hopkins method $\boldsymbol{H}$. The method estimates level of clustering of data points in the dataset. There are 3 different levels:

- H < 0.3: no clusters present in the data set
- $0.3 <$ H < 0.7: possible clustering
- H > 0.7: high level of clusters and nicely separable

Running Hopkins method on data sets of different measuring points, it was concluded that Hopkins value H was always in any case above 0.6 (60%) leading to the conclusion that method to be used favors clustering methods. The difference between some data points having H $>$ 0.9 and others having H > 0.6 results in how well the clusters in the dataset are separable - meaning some clusters would form bigger clusters. More about clusters and subclusters in Section 5.2.3.

4.3 Clustering Methods

4.3.1 Requirements

By the evaluation of feature spaces that data set favors by groupings of data points into multiple clusters, the decision is made to use clustering method in order to separate normal behavior from anomalies. When it comes to clustering, many different approaches and choices can be made. Before opting for one of them, a set of requirements needs to be set in order to reach a correct decision upon the most suitable clustering model being used as an element of *AutoSec*.
The set of requirements is presented in the following Table 4.1. The main decisive **requirement R1** is a clustering method with unsupervised learning, by means of not in need of labeled dataset. The cause for having the requirement R1 is uncertainty about the traced data used as a training data. Even in a normal execution of an ECU, anomalistic behavior can appear. Some of such cases will be presented Section 5.2.4.
Furthermore discussing about the **Requirement R2**, it is highly necessary since the system does not know how many groupings, clusters, exist in the dataset nor the location of data points in the feature space. Feature space is the coordinate system build using each feature as a separate axis. Thus, final algorithm must operate independently from knowing the number of clusters. The number of clusters could only be assumed based on other methods. More about in Section 5.2.3.
Requirement R3 is created upon deduction of dataset analysis by discovery of data points being distributed among clusters with uneven number of elements. Thus, the algorithm needs a method capable of clustering data set without prior knowledge about distribution of data points. The example is presented in upper-right subfigure in Figure 4.7. Examining alone cluster in bottom-right corner in this subfigure, it can be seen that it lays in the range where more than 50% ($\sim$ 30% + $\sim$ 23%) of Computation times are distributed in that section. However, overlapping that cluster with the distribution of S2S data points, it can be seen that this clusters consists of less than 1% of all data points in the dataset.
One of the main points to discuss when it comes to clustering of data points, separability of

data points is a topic to discuss. As previously depicted in upper-right subfigure in Figure 4.7, forming clusters are not linearly separable, thus **Requirement R4** is set that final algorithm needs to provide clustering for non-separable data sets.
Requirement R5 is not necessarily important and it represents only an optional requirement. The respect of this requirement will be used only as a preprocessing tool. More about preeprocessing of data sets will be discussed in Section 5.2.2. Last requirement R6 is more related for later industrial implementation than directly to limitations used on the Master Thesis work itself. Mainly, in the ECU used in ordinary vehicle, runs hundreds or even thousands of different Runnables, Events, Tasks, etc. Thus, a trained model for that high number of (potential) measuring points, needs to be delivered and examined in short period of time. In conclusion, the final algorithm needs to have low training time and ease of parameter changes needed for tuning parameters and thus obtaining improving results. Times presented in Table 4.1 are obtained with the PC: Intel i5-5370 and 64GB RAM memory for data set of a single Measuring point with 3183 samples.

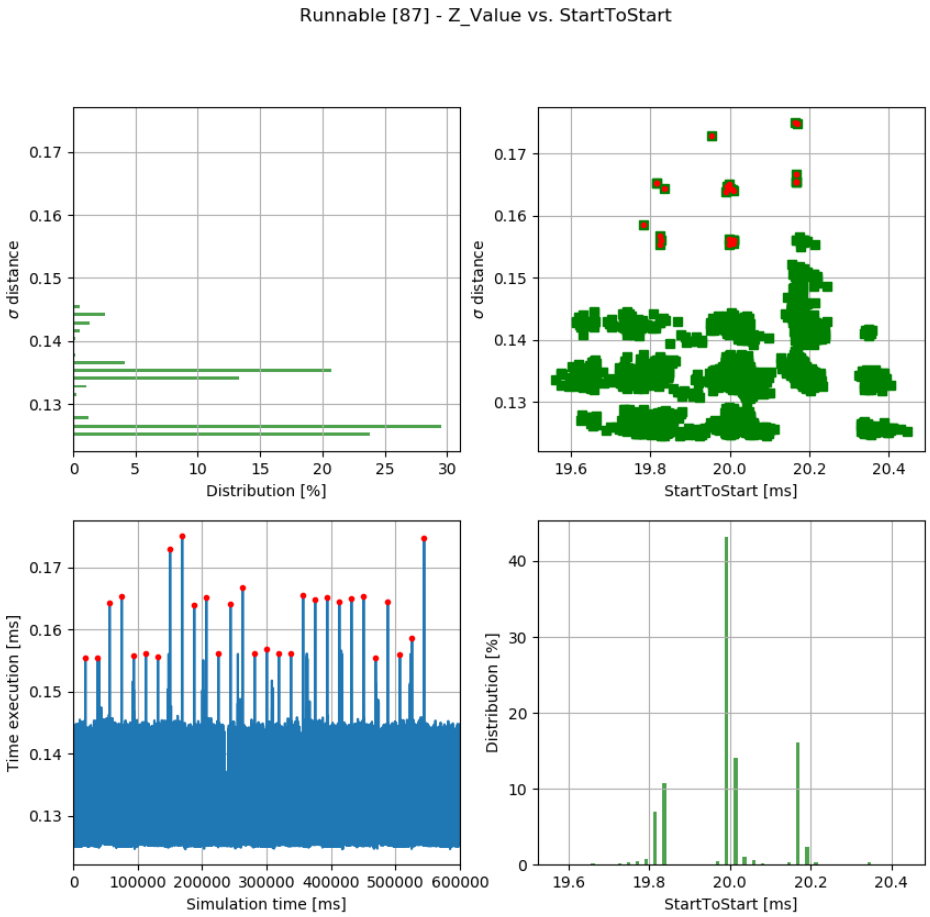


Figure 4.7: Histogram distribution of two features [Upper-left and bottom-right subfigures] Computation time needed by Measuring point over time[bottom-left subfigure] Overlapped distributions of feature 1 and feature 2 with each data point presented as a square in 2D feature space [upper-right subfigure]

Clustering Methods vs. Requirements						
	R1	R2	R3	R4	R5	R6
Methods	Unsupervised Learning	Unknown Number of Clusters	Unbalanced Dataset	Non-linearly Separable Clusters	Detected Outliers (training dataset)	Training time [3183 samples]
K-Mean	X		X	X		N.A.
k-Neighbors			X	X		N.A.
Spectral Clustering	X		X	X		1.71s
Affinity Propagation	X	X	X	X		3.12s
Gaussian Mixture	X		X	X		0.17s
DBSCAN	X	X	X	X	X	0.14s

Table 4.1: Requirements evaluation of different clustering methods

In following sections, there will be evaluation and discussion about some clustering methods with explanation of underlying technique they are using without deeper knowledge and mathematical explanations. At the end of this Chapter, a decision, about method to be used, will be reached, based on features of clustering methods and empirical outcomes they serve for dataset in the use case of the Thesis.

4.3.2 K-Mean Method

K-Mean clustering method [39] is a method being widely used in dataset with separable data. As presented previously in Table 4.1, this method requires prior knowledge about the number of groups in the dataset, meaning the number of separable clusters. Algorithm is based on iterable process of finding center points of clusters. In each iteration, each point in the data set will be clustered to the closest center point and being labeled accordingly to the cluster of belonging. The iterative process stops when the were no changes in labelings between multiple iterations or if the number of data points below the threshold have been changing the cluster of belonging repetitively for certain number of iterations in a row. At the end, the final outcome of clustering will be given.
In a case of K-Mean method, there is a possibility to sort (predict) new points into one of the clusters detected during a training phase. The function of *predict(...)*, work in the same as a part of training - it finds the closest center point of them all and then cluster the point into the cluster with the found center point. Thus, the whole feature space can be mapped about possible outcomes which data points belong to which cluster. Clusters do not need to be necessarily clearly separable, as it is depicted in the Figure 4.8. The main downside of this method in the use case in the Master thesis is that the number of clusters is not known in advance.

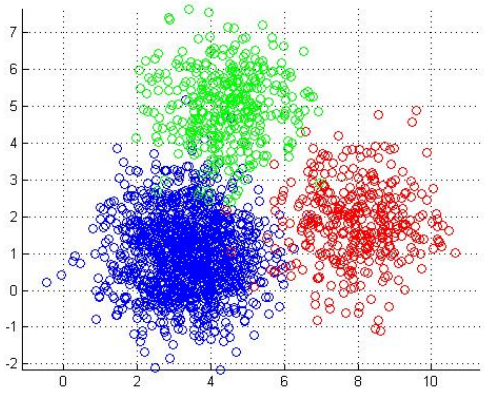


Figure 4.8: Example of K-mean clustering[1]

However, there are methods that overcome the setback of not having a prior knowledge about

[1]source: https://prateekvjoshi.com/2013/06/06/what-is-k-means-clustering/

the correct number of clusters. One of the methods is called Silhouette Method. The Silhouette method is based on K-mean methodology of clustering, by running a K-Mean clustering on the given set in the range of different number of clusters. The advantage of using Silhouette Method provides is that the prior knowledge of the correct number of clusters is not needed, but rather only a range of potential number of clusters.
As an example, the correct number of clusters is in range between 2 and 5. After obtaining the clustered data points for each case of number of clusters in the given range, an average distance of points within the same cluster will be calculated. The case of a certain number of clusters with the minimum average distance of data points within the clusters wins the arbitration as the most probable correct number of clusters for the given dataset. Thus, the calculated number of clusters will provide the best clustering results for the tested number of clusters that could possibly occur in the dataset. After exploiting Silhouette method, the obtained result can be in further in use the K-mean method. [40]

4.3.3 k-Neighbors

k-Nearest Neighbours (KNN) [41] method can be used for clustering and regression. Since regression is not in the scope of the Thesis, further discussion about KNN will be related to clustering only. The core idea behind KNN is to decide on cluster belonging of the examined point according to belonging of k nearest neighbors. Simplest example is 1-nearest neighbor - the new point will be sorted into the cluster to which belongs the closest point.
Similarly in case of k nearest neighbors, for $k > 1$, the method searches for closest neighbors. As the number of k closest neighbors that belong to the same cluster is reached, the new point will be clustered to the one. However, the value k needs to be chosen carefully, commonly empirically. The example of such misconception is given in the Figure 4.9. In such case, if $k = 2$, the new (green) point will clustered into the cluster with red points. However, in case of $k = 3$, the green point will be clustered into the cluster with blue points. By this phenomenon, initial clustering can oscillate without reaching a steady state during a *training* phase. Thus clusters needs a some amount of separation without having overlapping boundaries in between, what is the case in Figure 4.9.

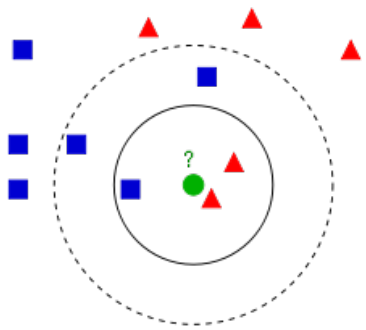


Figure 4.9: Example of k-Nearest Neighbors clustering[2]

[2]source: https://www.analyticsvidhya.com/blog/2018/03/introduction-k-neighbours-algorithm-clustering/

4.3.4 Spectral Clustering

Spectral Clustering [42] is unsupervised machine learning method that uses unlabeled data. Theory of graphs is underlying element of Spectral Clustering method. The algorithm used by this clustering method is to find the most optimal connectivity among data points in the feature space and upon that to group them into clusters. Eigenvalues and eigenvectors represent fundamental mathematical tool to construct graphs. The deeper discussion on mathematical level will not be led here, whilst the algorithm will be used as already built-in model and function in *Python* language. More about results of Spectral clustering will be presented in Section 4.4.

4.3.5 Affinity Propagation

Similarly to Spectral Clustering, Affinity Propagation [43] is unsupervised learning method that uses also unlabeled data. The method of clustering used by the Affinity Propagation is based on *message passing* between data points. Messages sends signals called *responsibility* and *availability* and by these two values, there are availability and responsibility matrices. Data points that would serve as an exemplar of the cluster will be stored in responsibility matrix, while other data points will be assigned to availability matrix with the value *how "appropriate" can the point be assigned to corresponding exemplar*. The algorithm is repeated in iterations until the cluster boundaries are unchanged for specified number of iterations, or the number of iterations in total reached max number of iterations specified priory to start of the training, too.

4.3.6 Gaussian Mixture Model

GMM [44] is also one of (semi-)unsupervised clustering methods. The idea behind GMM is to use data points density to describe them using Gaussian distribution. Thus, Gaussian Mixture (Model) represents a function consisting of multiple Gaussian distributions. Each of these k, $k \in \{1, 2, ...K\}$, distributions used to define Gaussian Mixture Model, represents a single cluster out of K clusters, how many there are in the dataset. The same problem here - the number of clusters is priory needed to be known. Similarly, as described in Section 4.3.2.For 1D data set, the Gaussian distribution is described with 2 values: μ - mean value, and σ - the deviation from mean value. However, if the dataset consists of 2 features, then the distribution is described using vectors and matrices, since the dataset is in 2D space. Similarly, for data set in higher dimensions, i.e. n, the distribution is described using a vector μ (the vector size $n \times 1$) and a covariance matrix Σ (the matrix size $n \times n$). Out of covariance matrix, the eigenvalues and eigenvectors can be calculated. Eigenvectors are used to calculate the orientation of the distribution in $n-$D space, while eigenvalues define the deviation from mean value in each of n dimensions, in local coordinate system anchored to mean value of the distribution. More about eigenvalues and eigenvectors could be read in [40].

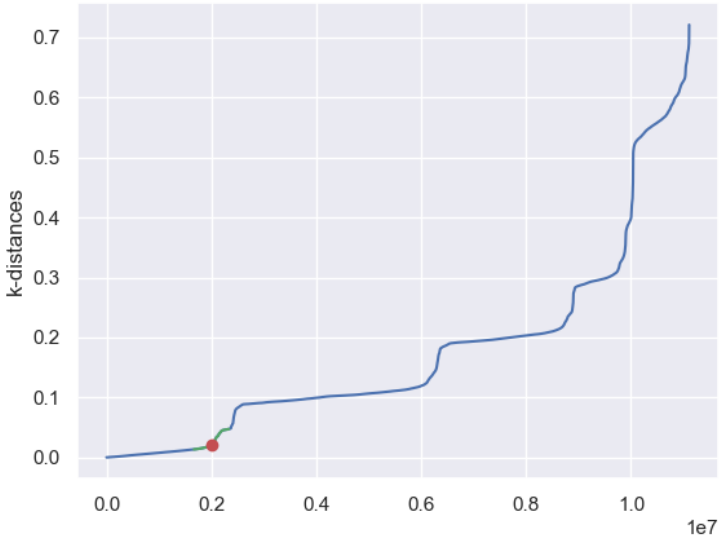


Figure 4.10: Example of k-distance graph with automatically determined ϵ value as a first "elbow"

4.3.7 DBSCAN

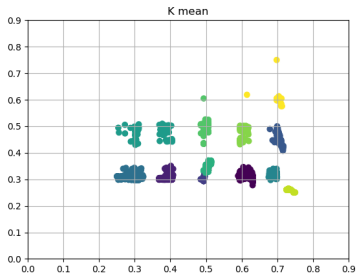
DBSCAN [45] is also one of algorithms that are unsupervised learning without labeled data. In addition, DBSCAN is immune to outliers in the dataset, and those points will not be sorted to the closest cluster although they are multiple σ distant from the cluster. The motivation for DBSCAN is described in the original paper [45] - *The application to large spatial databases rises the following requirements for clusterig algorithms: minimal requirements of domain knowledge to determine the input parameters, discovery of clusters with arbitrary shape and good efficiency on large databases.*
The algorithm is about "simulating" human detection of clusters by searching for dense group of points. Similarly, the DBSCAN algorithm searches points in the neighborhood within certain range. Firstly, the algorithm chooses random data points as core points, or "seeds". The following step is to examine remaining points if they are in the reach of cores/seeds. There are 2 different distances used in DBSCAN: direct reachability and indirect reachability. Direct reachability represents that the examined point is within specified range to the point of interest (*core points - seeds*). The DBSCAN algorithm requires one single input parameter, while there are others that are only optional. The requiring parameter is ϵ value representing the distance for examining reachability. The other (optional) parameter is *MinPts* - Minimum Number of Points that needs to be calculated as neighbors within the reachability.

In order to determine the best ϵ and MinPts value, there is a simple and effective heuristic methods that rely on determining those values for the "thinnest" - least dense cluster in the dataset. Methods for determining ϵ and MinPts are described in [45] (Section 4.2). Only brief

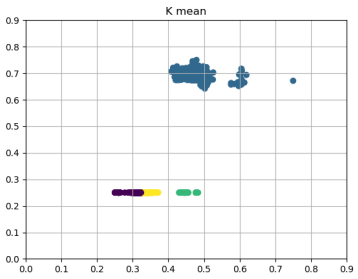
overview about ϵ determination will be given. The distance d will be calculated as a distance of a point p to its kth nearest neighbor. For a priory given value k, a function k-distance is calculated from the dataset to the real number, mapping each point to the distance from its kth nearest neighbor [45]. The obtain k-dist values are sorted and as such, they create a *sorted k-dist graph*. The "elbow" in the graph represents the most suitable ϵ value. However, remarked in [45], *it is very difficult to detect the first "valley"* ***automatically****, but it is relatively simple for a user to see this valley in a graphical representation.* Thus, the interactive and iterable approach for determining exact threshold point of ϵ is needed. The range of ϵ value is between $(0, 1]$. The example of k-distance graph is presented in Figure 4.10 - $k - distances$ on y-axis, and sample point in x-axis. More about details on this topic, can be read in [45].
The downside of DBSCAN is not having a possibility of classifying a new point that was not used during a training phase. The solution to this problem is described in the Section 4.5.

4.4 Clustering Results

Before evaluating different clustering methods on the dataset of timing features related to the Thesis's work, the data needs to be normalized and scaled down. Normalization is done between 0 and 1 - minimum and maximum value in the dataset is found and each point p in the dataset D is normalized (p-min) / (max-min). Since, we can not be certain that we have actual possible minimum and maximum value that can occure in the system, the dataset D will be scaled down to 50% and to keep the center point at 0.5 value. In other words, the normalization is actually done in range of 0.25 and 0.75 in each dimension of the dataset D. Throughout this section, different clustering methods described in short in previous section, will be examined in 2D feature space, i.e. S2S vs. Computation time, and Computation time vs. Total duration of preemptions ($\tau_{preepmtions}$). In figures to come, different clusters will be marked in different color, thus it is recommended to read the Thesis in colored version.
First clustering method to be examined is **K-Mean**. The results for S2S vs. Computation time and Computation time vs. $\tau_{preepmtions}$ is presented in Figure 4.11a and Figure 4.11b, respectively. The K-mean clustering method outcomes are run on an assumption that the correct number of clusters in the dataset is priory established. More about this in the following Chapter 5. As it can bee seen, due to imbalanced density and number of elements per cluster, K-Mean method does not provide good results. In addition, in Figure 4.11a, it can be seen in the upper right side of the Figure, a yellow dots are clustered into the yellow cluster although they are quite distant from the center of the yellow cluster and could be classified as a noise in the training dataset. Thus, K-Mean does not represent a possible element in the algorithm of the Thesis.
k-Neighbors - The result for the same combination of features - S2S vs. Computation time and Computation time vs. $\tau_{preemptions}$ are depicted in Figure 4.12a and Figure 4.12b, respectively. The sensitivity of very close points has a high influence on the algorithm not to provide quality clustering outputs. Thus, it cannot be used in clustering the features used in the Thesis.

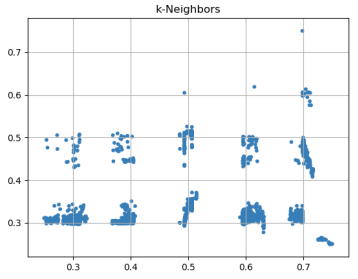


(a) Example of K-Mean clustering of features S2S vs. Computation time

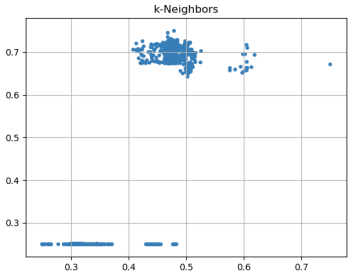


(b) Example of K-Mean clustering of features Computation time vs. $\tau_{preemptions}$

Figure 4.11: Example of K-Mean clustering of features different feature combinations in 2D feature space



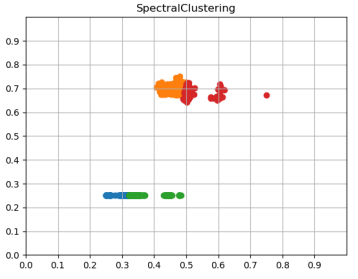
(a) Example of k-Neighbors clustering of features S2S vs. Computation time



(b) Example of k-Neighbors clustering of features Computation time vs. $\tau_{preemptions}$

Figure 4.12: Example of k-Neighbors clustering of features different feature combinations in 2D feature space

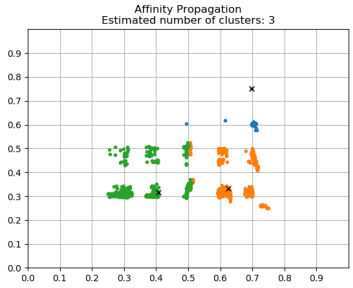
(a) Example of Spectral Clustering of features S2S vs. Computation time



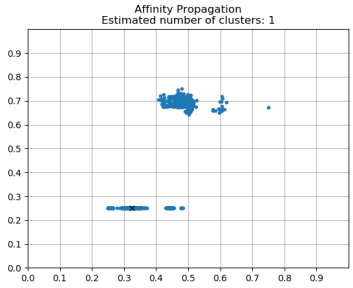
(b) Example of Spectral Clustering of features Computation time vs. $\tau_{preemptions}$

Figure 4.13: Example of Spectral Clustering of features different feature combinations in 2D feature space

Spectral Clustering - The result for the same combination of features - S2S vs. Computation time and Computation time vs. $\tau_{preemptions}$ are depicted in Figure 4.13a and Figure 4.13b, respectively. When it comes to Spectral Clustering outcomes, the results are similar to K-Mean. Although Spectral Clustering does not need number of clusters, it still does not provide quality output due to imbalanced number of elements per cluster. Due to poor outcomes, Spectral Clustering cannot be used as a element in the algorithm of the Thesis.
AP - The result for the same combination of features - S2S vs. Computation time and Computation time vs. $\tau_{preemptions}$ are depicted in Figure 4.14a and Figure 4.14b, respectively. In figures, clusters' center points are marked with the sign $\times$. As it can be seen according to found middle points, it was pulled towards the mean value of the cluster. The conclusion reviewing the outcomes can be drawn, the low quality results are obtained due to imbalanced data points distributions in the feature space. Since the algorithm is not capable of providing quality results, Affinity Propagation cannot be used as the algorithm in the Thesis algorithm.
GMM - The result for the same combination of features - S2S vs. Computation time and Computation time vs. $\tau_{preemptions}$ are depicted in Figure 4.15a and Figure 4.15b, respectively. Since GMM requires prior knowledge about the number of clusters in the dataset, it will be automatically calculated using Silhouette Method, as it was used by K-Mean algorithm. The range of possible number of clusters will be checked for the best outcome, and that value will be used for running GMM algorithm. In a case of Figure 4.15a, GMM has clustered data points based on the density of points. The yellow cluster is made of points with high dispersal, contrary to orange cluster with high density. However, in the Figure 4.15b, GMM clustering provided quality result. Since, results cannot be confident in any case of points distributions, GMM cannot be used as the algorithm in the Thesis algorithm.
The last algorithm to be considered is **DBSCAN**. The result for the same combination of features - S2S vs. Computation time and Computation time vs. $\tau_{preemptions}$ are depicted in Figure 4.16a and Figure 4.16b, respectively. The center points of each cluster are depicted using black squared points. As it has been remarked in the beginning of the Section, each cluster is marked in different color. However, since DBSCAN is capable of disregarding noise in the training dataset, the noise is depicted as black (round) points in Figures 4.16a and 4.16b. Contrary to previously examined Figures of other clustering methods, it can be noticed, that data points have been clustered with high quality. Ellipse in a color of clusters are just for representation purposes to mark the found soft boundaries of the cluster, since DBSCAN algorithm does not provide *prediction* (classification) of new data points. Thus, on right side of Figure 4.16a, there is a grey cluster with noisy points (black dot) being inside grey zone of soft boundary of the cluster. The point inside grey zone is found not to belong it during a training phase due to its distance from the closest point in the grey cluster is being higher from the threshold ϵ value. The soft boundaries are determined based on minimum and maximum distance of the point from the middle point of the cluster. More about this will be presented in the Section 4.5.2.

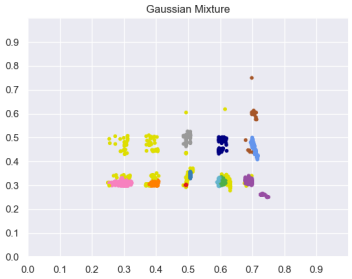


(a) Example of Affinity Propagation of features S2S vs. Computation time

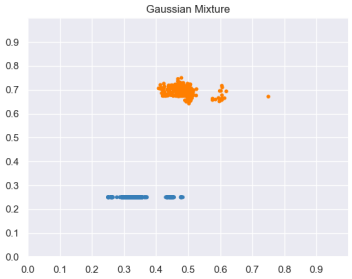


(b) Example of Affinity Propagation of features Computation time vs. $\tau_{preemptions}$

Figure 4.14: Example of AP of features different feature combinations in 2D feature space

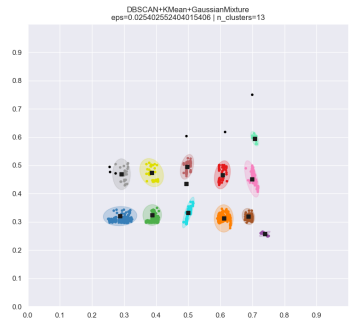


(a) Example of GMM clustering of features S2S vs. Computation time

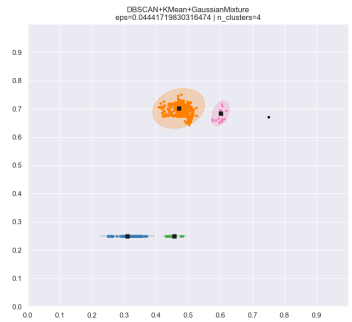


(b) Example of GMM clustering of features Computation time vs. $\tau_{preemptions}$

Figure 4.15: Example of GMM clustering of features different feature combinations in 2D feature space



(a) Example of DBSCAN clustering of features S2S vs. Computation time



(b) Example of DBSCAN clustering of features Computation time vs. $\tau_{preemptions}$

Figure 4.16: Example of DBSCAN clustering of features different feature combinations in 2D feature space

4.5 How to describe Clusters?

Defining algorithms to be used to cluster dataset, next question that is to be answered is how to use the obtained result so it can be used to predict new data. DBSCAN is a simple clustering algorithm that provides solution on clustering dataset in whole and not giving an solution how to cluster new data. Usually, new data will be clustered by DBSCAN using the whole dataset again. While this is no solution in our case, a new approach needs to be determined. Throughout this Section, a discussion around the question *How to describe Clusters?* will be led.

4.5.1 Number of Clusters

First element as the output of the algorithm is to know how many clusters exist to encapsulate the dataset elements' groups. These values are provided by the output of DBSCAN. However, the correct number of detected clusters can vary widely depending on input parameters for DBSCAN algorithm. Presented in Section 4.3.7, the main input parameter is ϵ value. Through the literature, there is an algorithm that helps to determine the most appropriate epsilon for the best clustering results using DBSCAN. The proposed algorithm is k-Distance measurements [46]. More about it can be read in [45].
The use, only, of the k-Distance algorithm will be evaluated here without examining deeper meanings of the algorithm. In base line, k-Distance algorithm evaluates distance to n-th closest element in the dataset to the examined data point. This is repeated for m different points creating the graph depicted in Figure 4.10. As features in the graph, there are multiple stairs, or elbows. According to [45], the most suitable ϵ value is in the elbow position of stairs. The value is commonly read from the graph, but in the case of this project all of this needs to be automatized as much as possible since in the real case scenario, there will be hundreds or thousands of measuring points and for each of them the appropriate ϵ value needs to be determined. Due to that, as part of the Thesis, a script was written to find the elbow in the system. Depending on the distribution of datapoints in the dataset, due to time constraints to develop the whole project, the script as elbow finder does not give the prefect result always. Considering this, the current status of the project provides semi-automatized learning.
During the learning phase, in case that algorithm gives too many clusters on the output with close grouping of clusters, a conclusion can be pulled that too small ϵ has been taken. Thus, an expert needs to reexamine the case by taking a look into the k-Distance graph an manually read the correct ϵ value and finally rerunning the training process with manually chosen ϵ value. With the elbow finder script, training time is reduced, but the training phase at the current stage needs to be taken with precautions to reevaluate the outputs manually in order to rerun training for certain measuring points with poorly chosen ϵ value.
At the end, evaluating that all ϵ have been chosen to minimize number of clusters and minimize the sparsity of data points inside each cluster, we reach the point to determine how to describe obtained clusters using DBSCAN for later Online/Offline use. More about this is given in the upcoming Section.

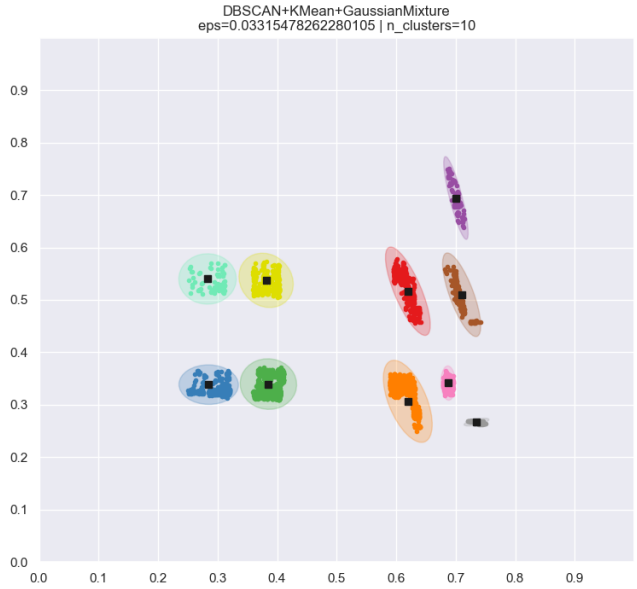


Figure 4.17: Example of DBSCAN clustering using a middle point and minimum and maximum distance to describe cluster zone

4.5.2 Cluster Measures

Describing obtained clusters can be done in many ways as it will be presented. In any case, center point of the cluster and the perimeter of the cluster needs to be defined, as well as the orientation of the cluster, i.e. rotation for angle α as depicted in the Figure 4.17. The orientation of the cluster is described using eigenvectors in both cases. Two different approaches to describe the cluster will be evaluated here.

First approach uses average value over all axes as the middle point. The perimeter is described as deviations over clusters local-coordinate system that is rotated for such angle α. In fact, the angle α will be not calculated, but rather matrix multiplication between point and eigenvector.
Similarly, the second approach uses middle point as the center between minimum value and maximum value of all axes in the clusters coordinate system. Thereby, the perimeter here is represented by maximum distances from the middle point to the most distant point in the cluster, according to the orientation of the cluster based on eigenvectors.
Now, knowing the middle point and perimeters, cluster boundaries can be drawn as ellipses in 2D space or ellipsoids in 3D space. For purposes of simplifications, only 2D example will be depicted here. The equation of ellipse is:

$$\frac{(x - x_0)^2}{a^2} + \frac{(y - y_0)^2}{b^2} = 1 \tag{4.1}$$

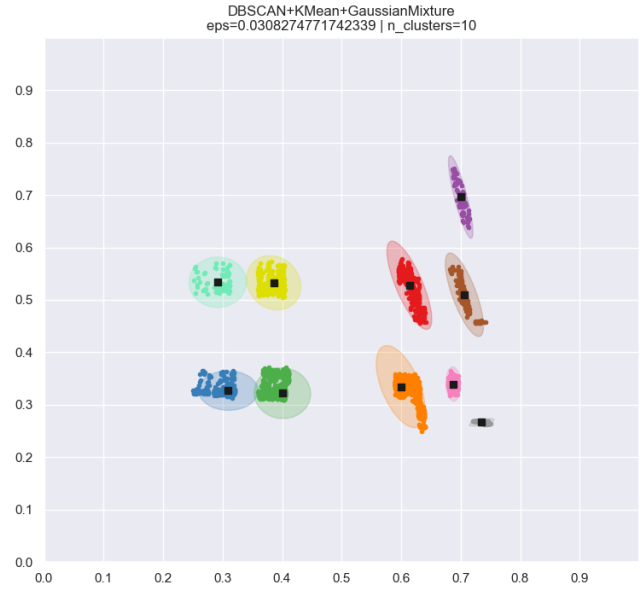


Figure 4.18: Example of DBSCAN clustering using mean values variances to describe cluster zone

In initial calculations of perimeters we have obtained a_0 and b_0 values, but what could happen is that some points can be out of the ellipse with these perimeters, so we need to increase perimeters with the same coefficient in order to maintain the scales of the ellipse. Thus, we can calculate the ratio how many times we need to increase perimeters with the same coefficient in order to envelope all points in the cluster. Afterwards, we obtain our final perimeter that describes the cluster. This approach is used in both cases.
The main difference between these two approaches is that in case of the first one, middle points tends to be favouring only one side of the cluster where the majority of data points is located. Thus, deviation will include all points in the cluster, but it will also include the side of the cluster where were no data points detected due to *"imbalanced"* data points in the cluster.
Regarding this disadvantage, in the Thesis, the second approach will be used that does not include the information where the most points in the cluster is located, but rather to evenly envelope the cluster with at least as possible empty spaces where no data points has been detected. With this, we can conclude that the algorithm has been prepared for the implementation and further analysis within the system, i.e. trainings, offline evaluations, online evaluations, etc.
Before leading a discussion on implementation, a broad picture of the ***AutoSec*** will be given. The overview of the proposed method - *AutoSec* is given in Figure 4.19.

The *AutoSec* can be used in *Offline* as well as in *Online* mode. The *Offline* flow consists of

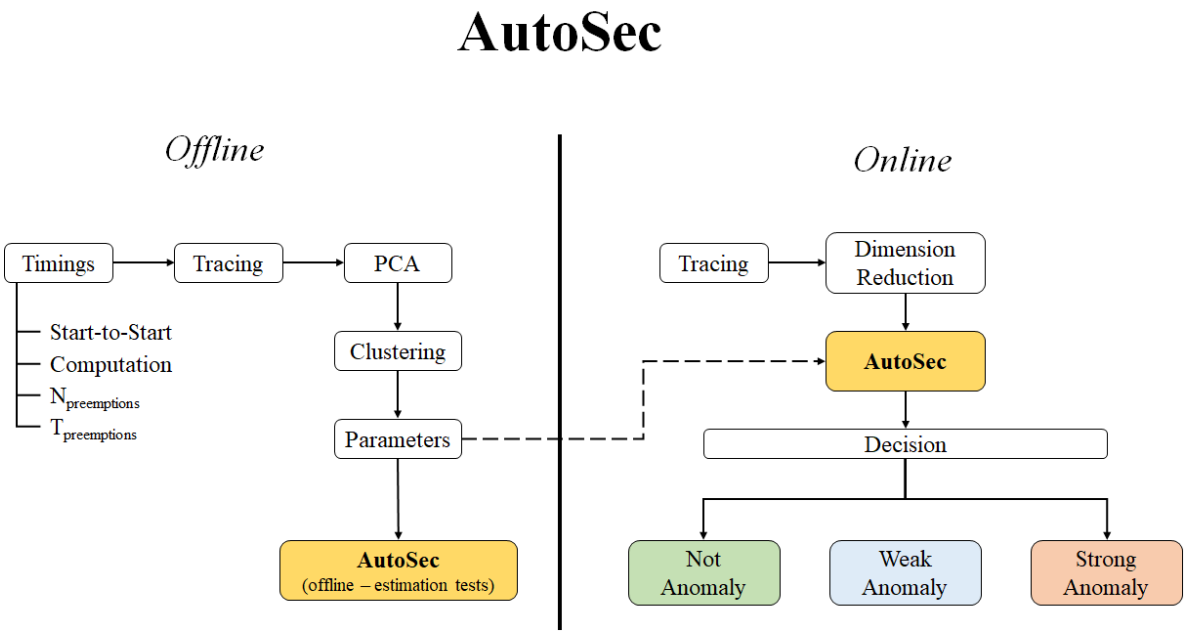


Figure 4.19: **AutoSec**

the measuring timing features of interest by running tracing of the running system. When the data has been collected out of the trace, a Principle Component Analysis (PCA) method is used to find needed parameters for dimension reduction from 4D to 3D feature space. Next step is to find clusters and describe them. The description is saved in form of parameters stored in *.h* file to be used on the ECU. The last step is to run *AutoSec in Offline mode* to evaluate the result. Remark, *AutoSec* can be also used in Offline mode, for evaluation of the system and anomalies in Schedulers during a design time of a system.
Regarding the Online workflow, the necessary parameters from PCA and Clustering are stored in separate *.h* file and used by onboard algorithm of *AutoSec* implementation. In online mode, in the correct stage of the algorithm, *AutoSec* checks every single instance of the monitored Entity. Thus, during a runtime, a monitored Entity is traced and obtained values from the measuring points, Dimesnion Reduction will be ran on four timing features to transform them into the 3D space. Next step is running *AutoSec* evaluation function, to measure the distance between new point and the closest cluster to the point. When the distance is measured, the decision will be reached whether the behavior is *Not Anomaly*, or *Weak Anomaly* or *Strong Anomaly*.
More about these steps in the following Chapter.

Chapter 5

Implementation

The implementation of the algorithm is done mainly in two phases. First is related to an offline algorithm development and system design. This is done in first 3 (dark blue) steps in Figure 5.1. The other two steps belong to the second phase of the algorithm evaluation during a runtime, in an online mode. The algorithm, the first phase as a proof of concept and workflow design, is done in *Python*. Second phase is online implementation of the algorithm using *C* code. The algorithm is added as a feature of AUTOSAR Classic implementation of the Vector Informatik GmbH. The test environment used for evaluation and verification of the algorithm is the Demo project provided by Vector Informatik GmbH. More about this in the following Section 5.1.
This Chapter is organized in the way to give an overview about testbed and the algorithm workflow. Following the system overview, each element will be explained separately going firstly through Training phase. During a training phase there are decisions to be made. Due to limitation of the working environment, Automotive industry in general, such decisions need to be automatized as much as possible due to high number of different elements being initialized by those decisions separately. When parameters have been determined, clustering will be executed providing the output information to be used in the *C* code for online algorithm that will be used during a runtime. The algorithm is firstly developed for offline use, the anomaly detection is ran on a trace. The trace is recorded execution of the code running on the ECU and *AutoSec*, as IDS algorithm, will be ran afterwards. After proving the capabilities and rounding the development cycle of the algorithm, *AutoSec* will be ran on the ECU and tested during a runtime. Brief overview of the cycle is given in the Figure 5.1. More about each of mentioned steps will be explained during separate sections throughout this Chapter.

5.1 Workflow

Before proposing the algorithm in whole, a few words need to be spoken about the testbed and working environment. The hardware being in use is the *Infineon* Evaluation board with the microcontroller from $AURIX^{TM}$*Family* - **TC277Tx** - red board in Figure 5.5. It consists of 3 cores running at 200MHz. The microcontroller is used under the AUTOSAR in ECUs in production lines. The evaluation board was used instead of the ECU for available ports to use external debuggers for tracing the operation of the program running on the microcontroller.
The debugger is used with the purpose of porting the code, debugging and tracing.*iSystem*

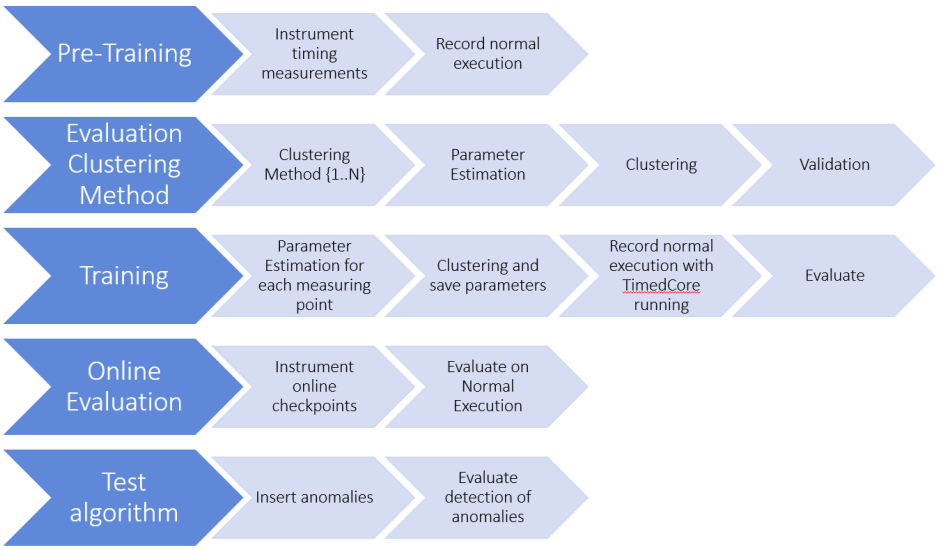


Figure 5.1: Process overview

iC5000 is debugger used in the testbed - blue device in Figure 5.5. The debugger iC5000 provides a capability to port the new code into the MCU and to execute the code line by line. Beside standard debugger features, it was able to trace specific variables in the program - *volatile* variables. Volatile variables are created at the beginning of the program and they live until the end of the code execution. Any part of the programme can access these variables explicitly, thus it can change its value any time during the execution and it is undergone under the compiler optimizations. Therefor, tracing of different measuring points in different parts of the code (different *.h* or *.c* files) is possible throughout a single variable with proper mapping of currently active measuring point and its status. Afterwards, the mapping of the variable will be parsed in the debugging environment - *winIDEA* (Figure 5.2). Using the proprietary software from iSystem - *winIDEA*, the recorded trace can be exported in the *.BTF* file for later evaluations and examinations. More about this, will be discussed in Section 5.2.

Next element is CANoe - a Vector Informatik GmbH propriatory software for tracing communication on the bus - Figure 5.3. Communication can be between real ECUs, as well as simulation of other communication nodes (other virtual ECUs) communicating between themselves and/or with other real target (i.e. real ECU or evaluation board in the case of the Testbed used as part of the Thesis) - Figure 5.4. The communication trace between real communication node(s) and virtual node(s) is done using *Vector VN5610 Ethernet/CAN Interface - 100BASE-TX/1000BASE-T*. The device is depicted as a grey-red box in Figure 5.5.

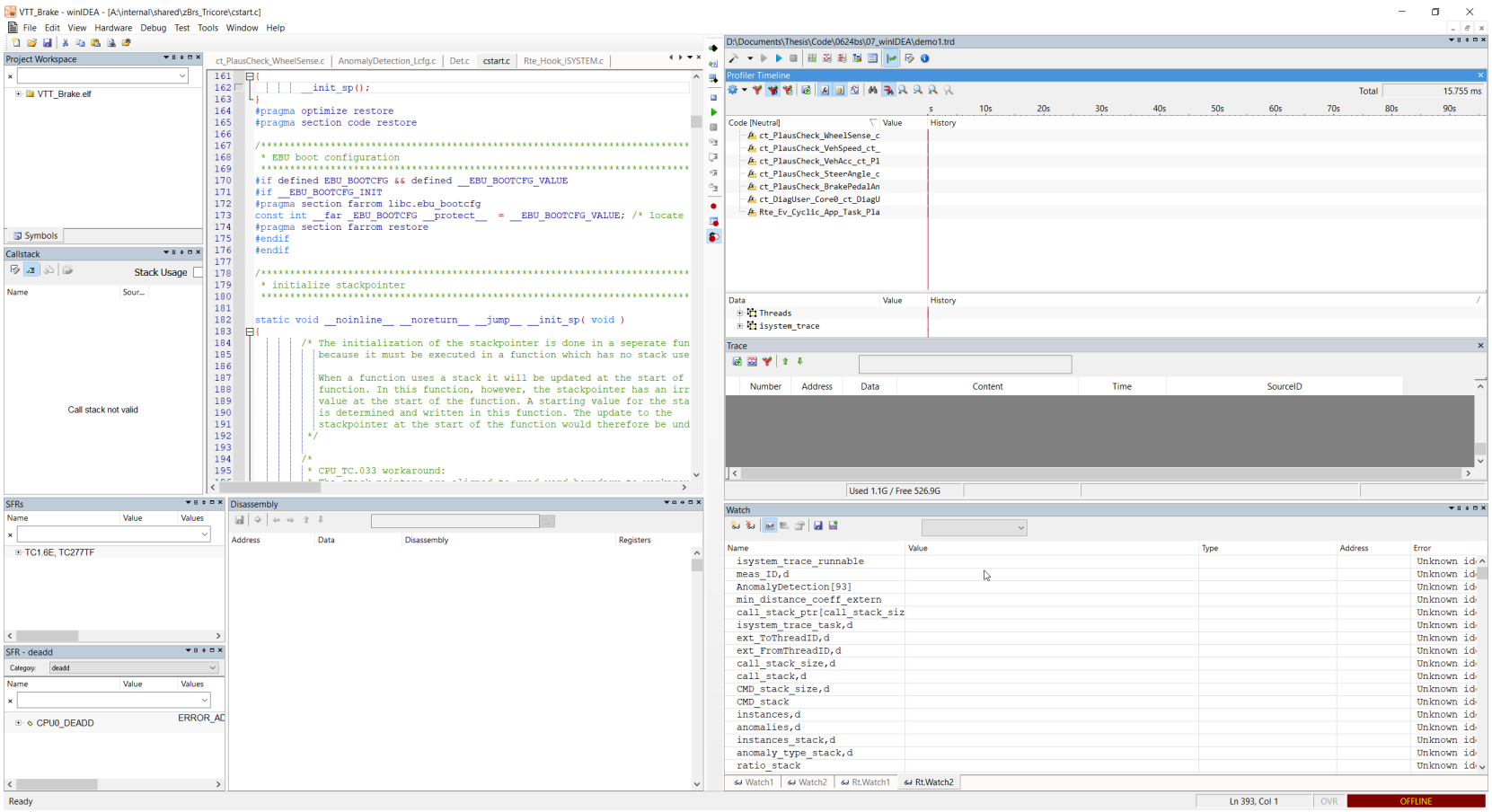


Figure 5.2: winIDEA working environment

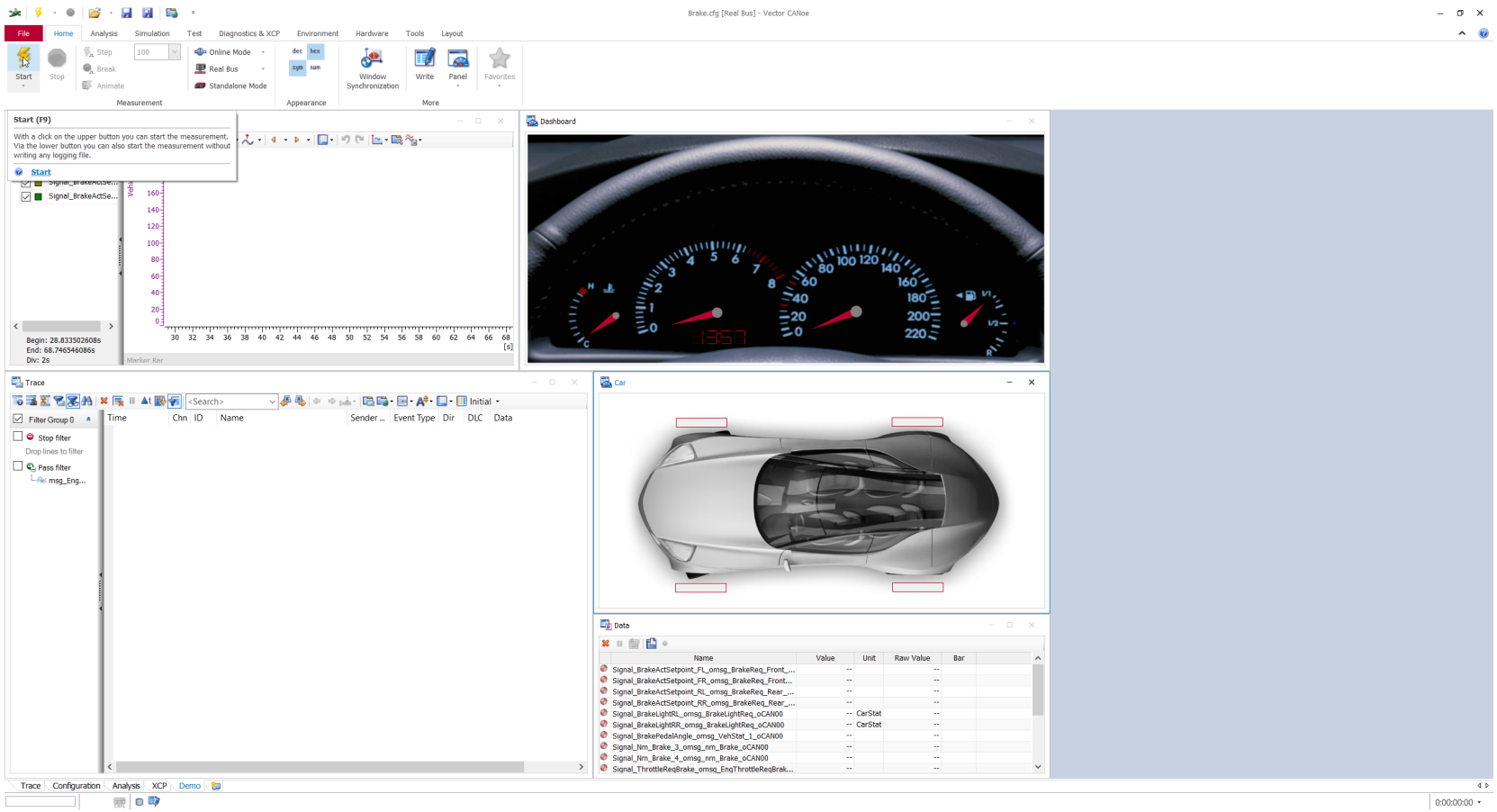


Figure 5.3: CANoe Demo working environment

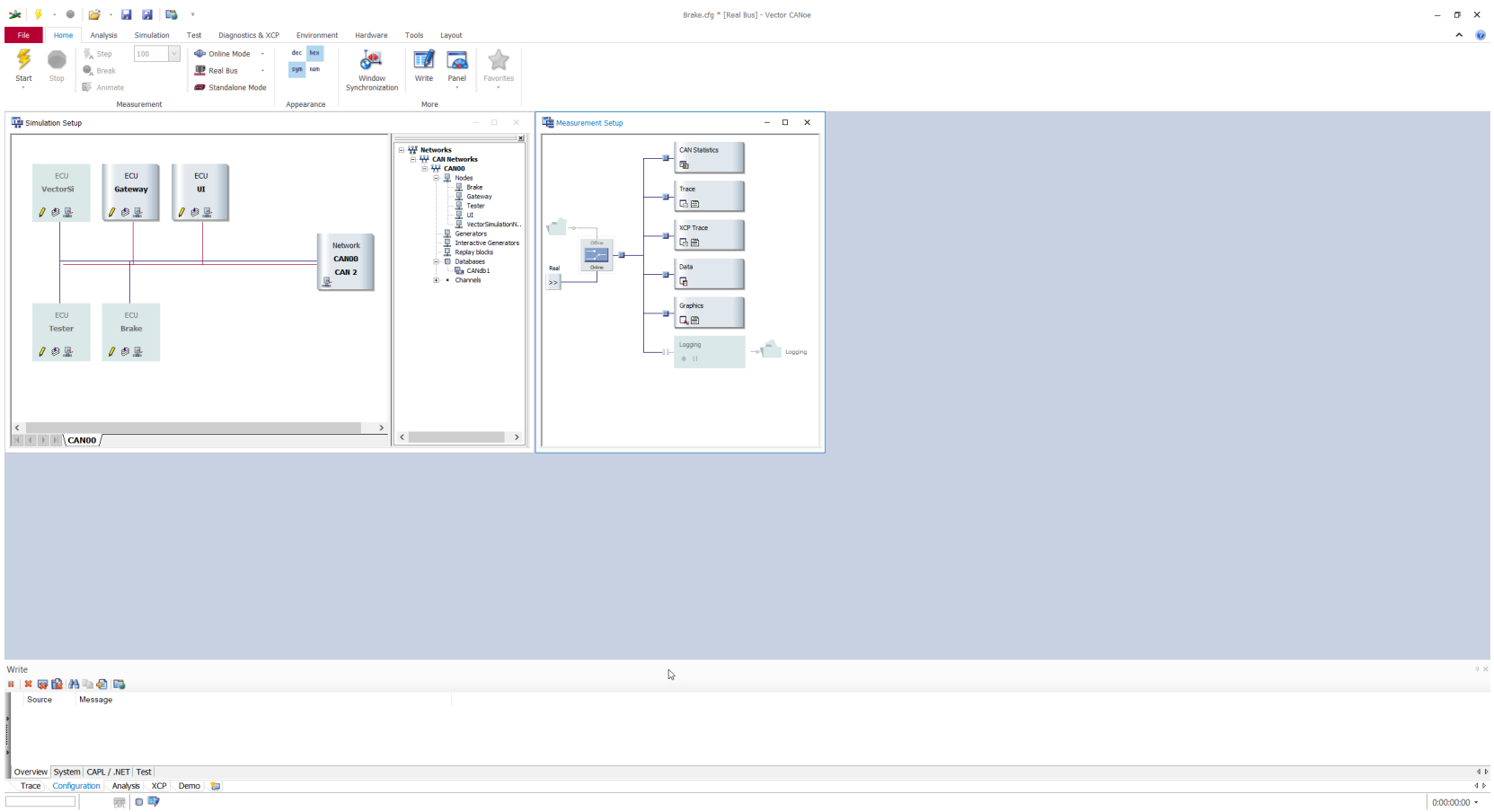


Figure 5.4: CANoe network communication setup

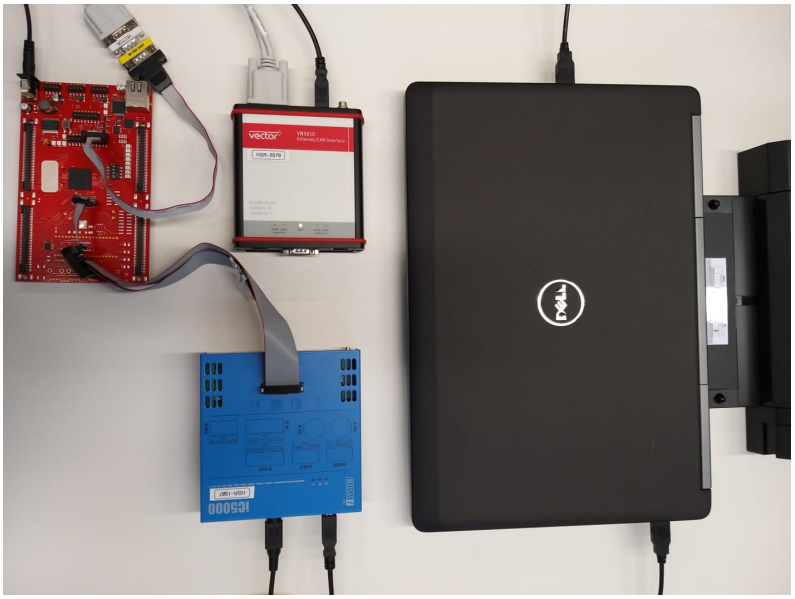


Figure 5.5: Testbed Setup

Connection of the hardware is presented in Figure 5.5. All devices, *VN5610 Ethernet/CAN Interface* and *iSystem iC5000*, are connected to the PC. Hardware components are controlled and connected to different software programs running on the PC under the Windows 10 operating system. The PC consists of Intel Xeon CPU E3-1545M at 2.9GHz and 64GB of RAM memory. The programs used during the Master Thesis are: *DaVinci Configurator, CANoe, winIDEA, Microsoft Visual Studio, Visual Code.* Before giving a brief information about each of softwares being used, a remark regarding AUTOSAR implementation is needed. The AUTOSAR as such is only a standard, mainly list of rules and requirements as well as specification about how-to implementation of the standard. The implementation of the AUTOSAR is provided by different companies. Vector Informatik GmbH is a provider of implementation as a proprietary software called *MICROSAR*. Further in the Thesis, a reference to MICROSAR is related to Vector Informatik's implementation of the AUTOSAR.
The *DaVinci Configurator* is a proprietary software from Vector Informatik GmbH, as well as *CANoe*. *DaVinci Configurator* is used for configuring MICORSAR components and interconnection with SW-Applications. *DaVinci Configurator* at the end of configuration, generates Visual Studio project for further potential code development and finally compilation of the code. This process is followed by porting the compiled code's *.hex* file into the microcontroller using *winIDEA* working environment. Since there is never a single ECU in a car, *CANoe* is used for simulating other ECUs and the communication running on different buses coming to the real target (AURIX board) - as it is depicted in previously described Figure 5.5. MICROSAR configurations were not part of the Thesis, so no further discussion would be undergone in this field, but rather direct generated code manipulations by inserting code necessary for algorithm implementation and instrumentation.

The testbed is organized in a way that *CANoe* simulates other two ECUs operating only

as a communication nodes. The topic of the Thesis is not directly concerned about the execution of those two (virtual target) ECUs, but rather their interconnection to the real target - code running on the AURIX board. Two virtual ECUs control vehicles engines and *Body* functionalities, while the real target operates with brakes. After the input of brake pedal has been processed by one of the virtual ECUs, the value is send to real target to its Braking Application. The brake force is calculated in the real target and the response is send back to virtual ECU. The communication between virtual target and real target is controlled by *CANoe* communicating to the real target over *Vector VN5610 Ethernet/CAN Interface - 100BASE-TX/1000BASE-T*, which generates CAN messages being send to the real target, as well as processing received CAN messages from the real target and providing the information back to *CANoe* working environment for further use.
Having a data set being examined and a boundary of *normal* behavior of the execution being found, the algorithm as a process will be given and explained in steps of it's development. The algorithm workflow is presented in the following Figure 5.7. The presented workflow corresponds to one iteration of the Training phase. More about each step, will be discussed and explained in the following Section 5.2 - Training.

5.2 Training

When it comes to conventional Machine Learning stages (pipeline), three phases: training, evaluation and test. Training is conducted on the new data set used for training a system and the evaluation is the second phase with additional data to evaluate how good learning in the training phase is done. If the result is not satisfying, the training phase will be repeated with adapted training parameters. Finally, the when the outcome of evaluation phase is verified, the learned will be tested on totally new data set to examine results on the data that has not been included in any way with learning - not in training phase nor in evaluation phase.
Contrary to standard Machine Learning pipeline, the evaluation phase is not part of clustering methods. As mentioned in Section 4.5, clustering is done once by making groups (or clusters) into separate units. Clustering is a method that requires rerun if new data is available. Whilst the requirements of the problem state only the evaluation of the new data set upon previously learned model, during a runtime a classification method is required. Clustering method defines boundaries of the group of data points, while classification finds the boarder line between two regions and all beyond the boarder line will be certainly sorted in one of the regions.
The difference is depicted in the Figure 5.6. On the left hand side, a simple classification model of linearly separable data points. In the the example, all data points below the dashed line are to be classified as one class (red dots), whilst the data above the dashed line is to be classified as another class (grey squares). Thus we can evaluate new data points in which class they belong. The new data point can occur any place in the data space. Contrary to the classification, clustering method determines hard boundaries of "classes". The example on the right hand side of the Figure 5.6, presents that if a data point found in upper left side of the graph, it does not belong neither to red dots nor to grey squares and thus, re-clustering needs to be done. Based upon chosen clustering method, a new data point can be joined to the corresponding cluster. The downside of operating as described is that all data points need

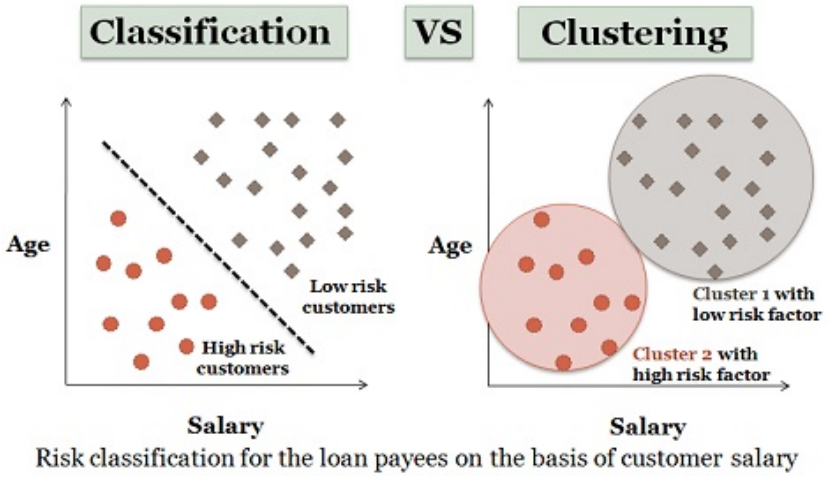


Figure 5.6: Classification vs. Clustering[1]

to be included in re-clustering in order to reach to most precise decision upon clustering the new data point. During the re-clustering, some data points being part of one cluster, can change its belonging to another cluster in the dataset. Thus, determinism and certainty is not guarantied. Summing up, classification provides certain and simpler sorting method of a new data point, while clustering method defines hard boundaries of groups of data points. Since the need to have a hard boundary of groups in order to differentiate normal behavior, data points within hard boundaries of many different groups, and abnormal behavior being outside these boundaries, a method of classification of new data points into determined clusters needs to be proposed.

Taking mentioned different advantages and drawbacks of clustering over classification, the algorithm can be proposed - Figure 5.7 - ***AutoSec***. Different clustering methods have been discussed in previous Chapter 4 - Concept and Design, DBSCAN has been chosen as the one which fulfills all requirements and results in the best outcomes. The first step is to run DBSCAN, as chosen clustering method, on the new data set. Following determined clusters, different evaluations will run to determine parameters to describe detected clusters, resulting in generated *.h* file to be used in the MICROSAR. More about each of theses steps will be discussed and explained through out following sections of this Chapter.

5.2.1 Semi-automatized parameter estimation

After recording the trace of normal execution of the measuring point (Task/Event/Runnable), a DBSCAN parameters needs to be estimated and provided to DBSCAN for successful clustering - Steps 1 and 2 in Figure 5.7. The parameters in need are Minimum Number of Samples, Minimum Neighbors and ϵ. First two parameters are empirically determined during the evaluation of algorithms that Minimum number of samples being 3 and Minimum Neighbors being

[1]Source: *TechDifferences: Difference Between Classification and Clustering*

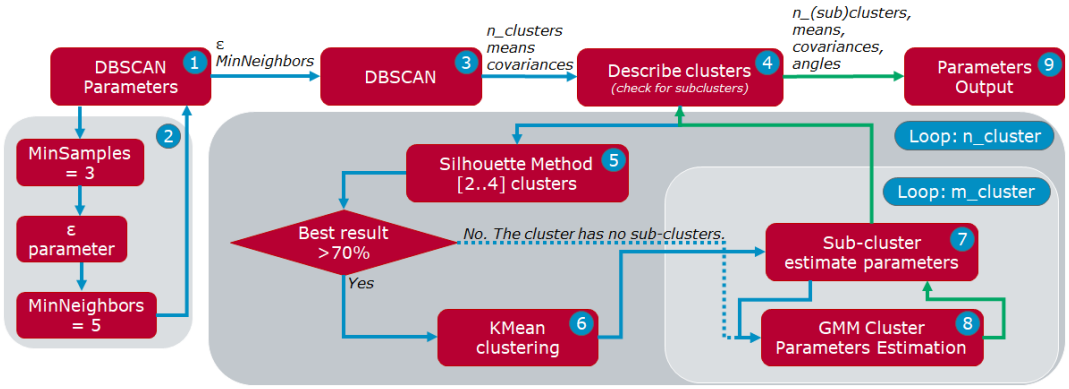


Figure 5.7: ***AutoSec*:** Proposed algorithm flow for Anomaly Detection as a Host-based Intrusion Detection System

5 results in the best tradeoff between coarse and fine clusters, as well as total number of outliers in the training data set. If Minimum number of samples is higher, the clustering will result in less number of clusters, which does not represent bad result. However in combination with Minimum number of Neighbors can result in some data points on the edge of the cluster to be discarded as outliers. Beside this, the two parameters highly depend also on the number of points in the data set that is dependent on the length of the trace. Thus, these two parameters are not automatically estimated, but rather empirically determined depending on the use case, i.e. trace elements, and *hard coded* into the algorithm.
Independent on the use case, but rather dependent on the data distribution in the space (feature space - each feature, i.e. computation time represents one axis), ϵ can be determined based on mathematical statistics. The methods used to find the most suitable ϵ is called k-Distance graph. The example is depicted in Figure 5.8. The k-Distance method evaluates dispersion of data points in the feature space. The method calculates the minimum distance to the k-th closest neighbor. Iterating the calculation over data points in the data set, the calculated distances are obtained and those form a graph as presented in Figure 5.8. In the y-axis are values of distances and the values are sorted in ascending order. Due to computational and memory limitations of the used hardware, not all data points could be used for creating a k-Distance graph, thus a certain number of data points will be randomly chosen from the training data set to obtain distances for k-Distance graph.

Meaning behind the k-Distance graph is showing how close/far are data points within the data set. As it can be seen in the Figure 5.8, there are stairs in the figure. Rough estimation determines how many steps there are, that much clusters are in the data set. This is only side effect that can be used with high certainty due to limitation how many and which data points have been taken into the calculations. However, the data points within the same cluster form similar distances within them. Thus, a first knee/elbow, going from closer distances to larger distances, represents the distance between two closest clusters. The point of first elbow is presented with the red point in the Figure 5.8. Contrary to that, the last elbow represents the sparsity of the whole dataset. Due to that reasoning, the proposed algorithm is interested in finding the very first elbow in k-Distance graph. The distance value (y-axis value) of the

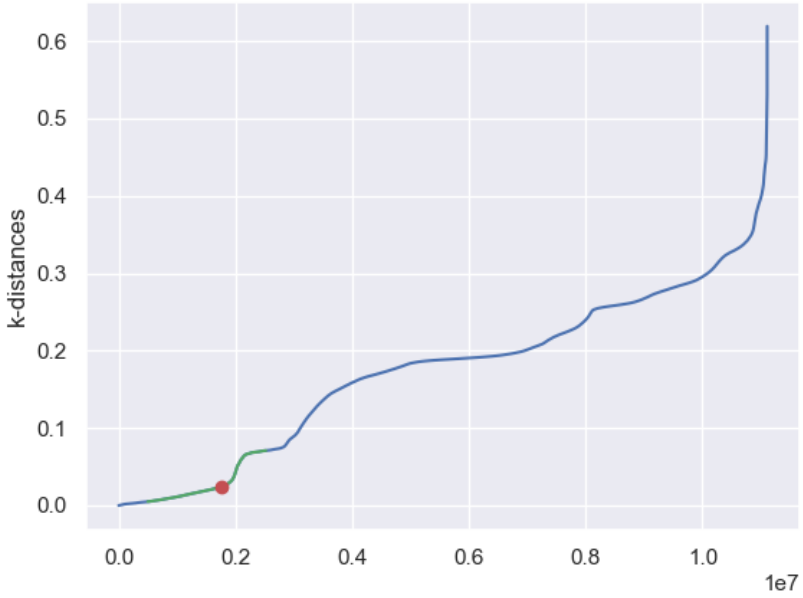


Figure 5.8: k-Distance graph calculated on one of the measuring points from the Thesis

first elbow in the k-Distance graph represents the suitable ϵ value to be used for DBSCAN. More about ϵ and DBSCAN can be read in [45].

Unfortunately, dependent on the data set itself, ϵ value of the first elbow might produce too many clusters (Figure 5.9), and some part of them are in a close proximity, while the others are quite distance forming another dense group of clusters. The conclusion reaches the point that those clusters in close proximity would need to be merged and thus forming smaller number of clusters in more intuitive way. The example is given comparing Figure 5.9 and Figure 5.10, using lower and higher ϵ values, respectively. The downside of the ϵ estimation step in *AutoSec* algorithm, is the external expertise is needed to evaluate chosen ϵ value. Thus, this step is called *Semi-automatized parameter estimation*, since the ϵ will be chosen to the best capabilities of k-Distance method and in that way minimize the time to estimate thousands of ϵ values for thousands of different measuring points in the System. However, external expertise is needed to validate and verify the automatically chosen ϵ value whether it produces clustering outcome with as good as possible trade-off between: distance between clusters, size of clusters and number of clusters. This part can be called *Validation* phase, corresponding to the standard Validation phase in Machine Learning pipeline. The main difference is that, best to author's knowledge, no automatic method exists to validate chosen ϵ with constraints of trade-off between: distance between clusters, size of clusters and number of clusters. The drawback of *AutoSec*, in some specific cases, an ϵ would need to be manually chosen with the higher value reading it from the second, third, or later elbow in the k-Distance graph.

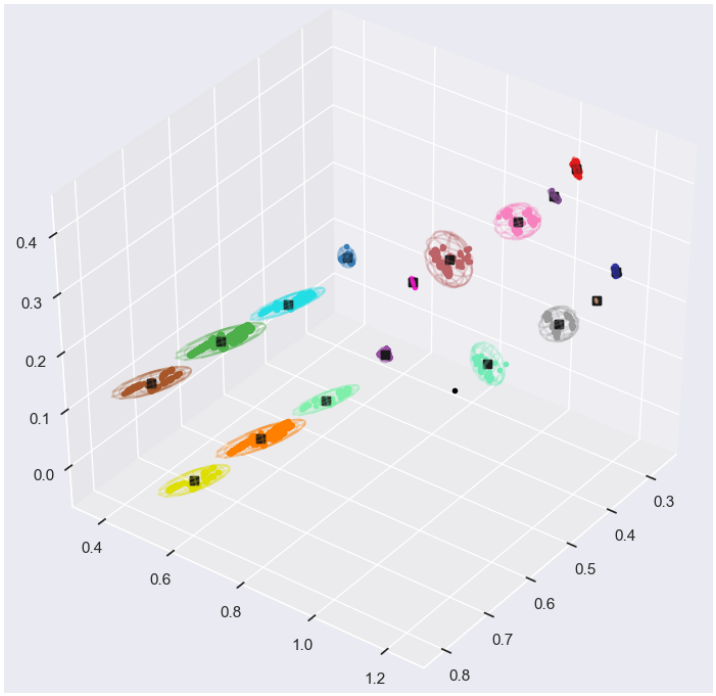


Figure 5.9: Results on Runnable 93 training output when chosen ϵ has **lower** value

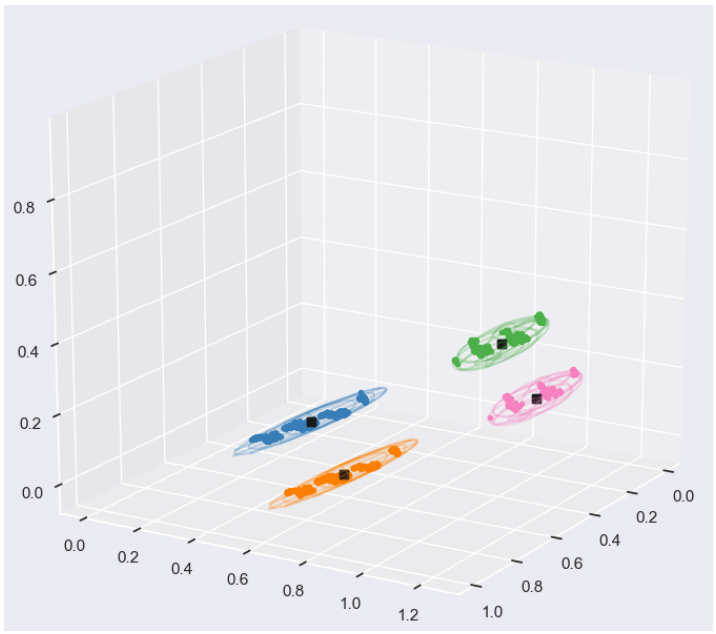


Figure 5.10: Results on Runnable 93 training output when chosen ϵ has **higher** value

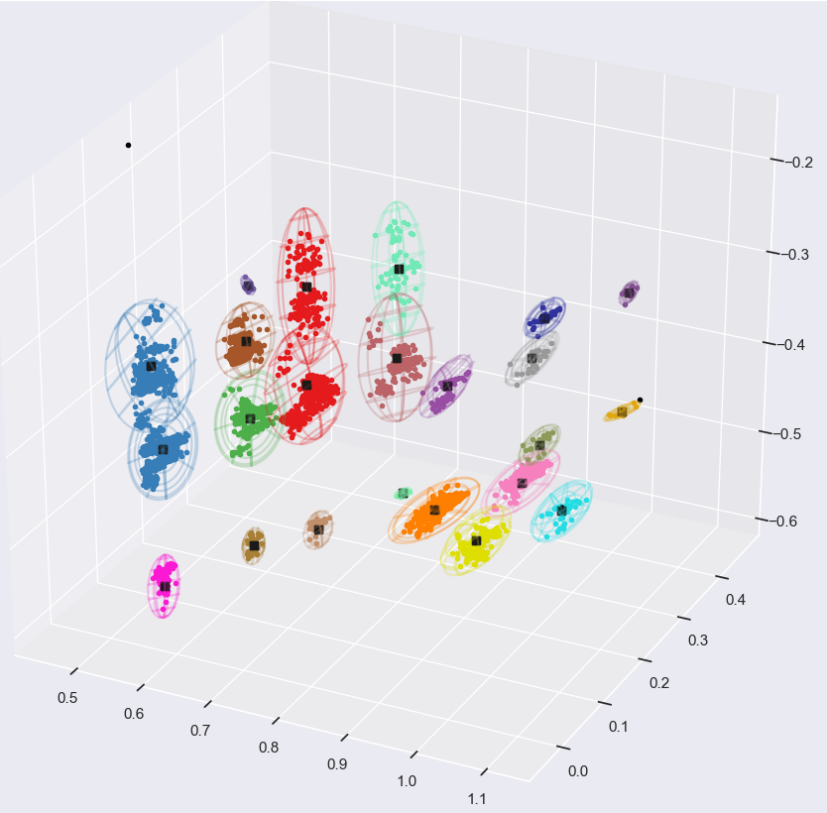


Figure 5.11: Clustering by DBSCAN in 3D feature space

5.2.2 DBSCAN as Pre-Processing Method

Tracing normal execution and behavior of the System, it can not be guaranteed that there is no abnormal behaviors already within the *normal* trace, or some highly rare instances of normal behaviors, i.e. initialization phase. In order to filter such elements out from the training data set, one of the requirements *(R5)* in Table 4.1 was that the chosen algorithm should be able to detected outliers in the training dataset. Since the DBSCAN possess such feature, it can be said that DBSCAN as clustering method is a filter as part of the Pre-Processing phase with benefit being clustering methods as well - Step 3 in Figure 5.7. The example is depicted in Figure 5.11. Clusters are colored and bounded, while black round dots represent outliers detected in the training dataset. In the upper left side of the figure, truly a single data point is excluding itself from the rest being an outlier filtered out by DBSCAN clustering. Thus, it will not be included in describing space of the normal execution in the feature space.
After determining clusters, colored data points in the Figure 5.11, clusters needs to be described. The solution is already presented in the Figure 5.11, by defining middle point (black squares) and boundaries of the cluster (colored lines) that encapsulate data points belonging to the same cluster.

5.2.3 Optimal Number of (Sub-)Clusters and their measures

After detecting clusters in the data set and mapping data points to its corresponding cluster, as well as disregarding outliers present in the training data set, next step is to describe clusters by its middle point and size, as described in Section 4.5 - Step 4 in Figure 5.7.
Examining Figure 5.11, especially taking *blue* and *red* clusters into the consideration, it can be seen in the given Figure, that each cluster is described using two boundaries embodying its data points. The explanation will be given on the *blue* cluster. Taking a closer look on it, data points forming blue cluster are two groups that can be considered as two subclusters. The reason behind these two subclusters are not recognized as two different clusters is due to the data points between them forming a *bridge* between them and thus connected these two (sub)clusters. Thus, these two subclusters form a single bigger *blue* cluster, in comparison to *brown* and *green* cluster that are highly close, but no bridging data points in between to connect them.
At this point, there is a reasoning why two boundaries have been used to describe the blue cluster instead of single one. The reason is: *blue* cluster is formed out of two subclusters that each of them can be described with different Gaussian distribution function. Thus, the *blue* cluster can be described as mixture of combined different Gaussian distribution functions. Using the approach describing big clusters as mixture of different Gaussian distribution functions, gives the freedom to describe any shape and form of cluster that is not necessarily rounded in thus to be described with only a single Guassian distribution function. The problem aroused when, *AutoSec* reached the point to describe such clusters as the *blue* cluster in the following Figure 5.12. Such cluster needs to be described using multiple different Gaussian distribution function. The following part will be executed n times *(n loops)* corresponding that n different clusters are found in the data set.

In order to do so, the Silhouette Method is used to estimate how many subclusters the big cluster has, if any (*Best result > 70%)*[2] - Step 5 in Figure 5.7. The meaning is how many Gaussian distributions are needed in order to describe the big cluster. The Silhouette Method runs K-Mean method with many different values for K (number of clusters) only on the data points belonging to the big cluster, i.e. *blue* cluster in the case of Figure 5.12. The Silhouette method will iterate K-Mean clustering over K being in range $[2, 4]$. These values needs to be predefined in a case of the algorithm, depending on how many subclusters could be detected in a single cluster. If number of subclusters is to big, the overfitting can be reached and overloading final outcome of *AutoSec*. Thus, a reasonable number of subclusters needs to be defined. The measure to determine the number of subclusters used by Silhouette Method is how close each point in one cluster is to points in the neighboring clusters. The visual results of the outcome is presented in Figure 5.13. If Silhouette Method outcome, for any value of K in the predefined range of potential number of subcluster, surpasses the predefined threshold of 70% (Hopkins value), the corresponding value of K will be taken into the further use.

If K has been determined as the result of a big cluster having subclusters, a K-Mean clustering for the calculated K-value will be taken - Step 6 in Figure 5.7. Following the algorithm

[2] 70% (0.7) is taken as a threshold based on the Hopkins value as the level of highly separable clusters
[3] Source code used for running Silhouette Method: *scikit Learn: Silhouette Method*

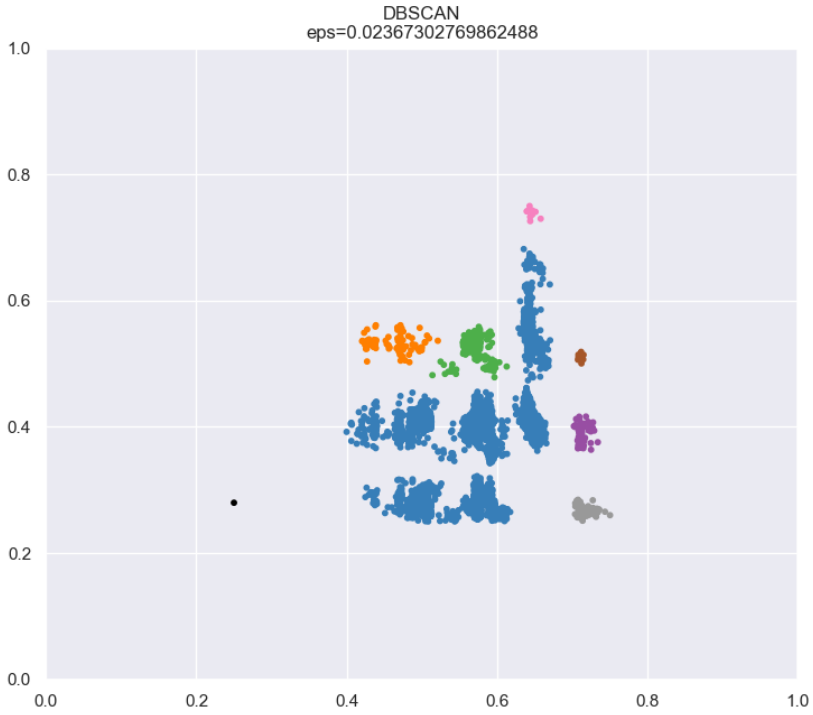


Figure 5.12: Clustering by DBSCAN in 2D feature space

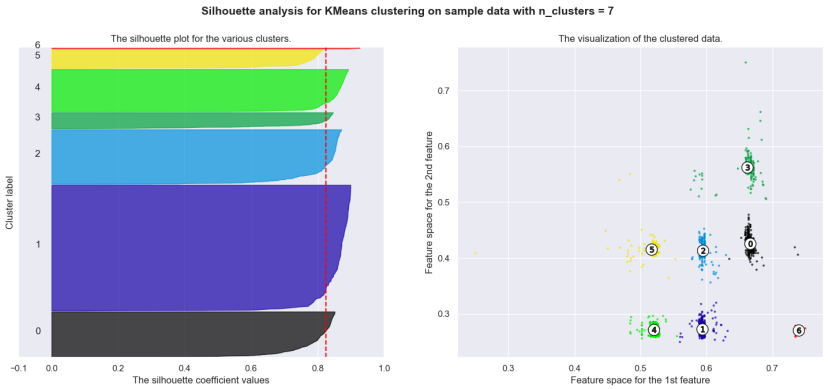


Figure 5.13: Output result of Silhouette Method[3]

workflow furthemore down the line, steps 7 and/or 8 are reached in Figure 5.7. In case that m different subclusters exists, GMM will be ran on each subcluster separatly m times *(m loops)*. Otherwise, it will be ran only once on the cluster. The outcome of GMM provides us eigenvalues, eigenvectors, medians and variances.
At this points, there are two possibilities to describe a cluster as discussed in the Section 4.5.2 - Step 8 in Figure 5.7. The final decision is made to use a single middle point and max deviation of a data point in a (sub)cluster from the middle point of the (sub)cluster to define the size of the (sub)cluster in each dimension of the feature space as an radius value of ellipsoid that bounds the data points. However, GMM is needed in order to determine the orientation of the cluster in the feature space using a eigenvector obtained using a GMM.

5.2.4 Training Output

By running Steps 4 through five, six, seven and eight, the description for each cluster and subcluster is determined and calculated. Thus, measures are obtained and ready to be generated to output to be used in implementation for testing the algorithm firstly in Offline mode (do the trace followed by running the algorithm) and afterwards in Online mode (running the algorithm in runtime). The final Step 9 in Figure 5.7 is to generated corresponding *.h* file to be used in MICROSAR. *Python* script is used to generated such *.h* file. The organization of data is in the following way:

- Cluster: described with the C structure contained the information about the number of subclusters, an array of middle points, an array of variances (radius values) and an matrix (array of arrays) of inverse eigenvector to be used to manipulate new data points transfering it to the local coordinate system docked for the middle point of the cluster
- Measuring point - set of clusters: described as a structure consisting of ID value of the corresponding measuring point, an array of pointers where each points to corresponding structure of the cluster, a matrix (an array of arrays) consisting of PCA values and finally a matrix (an array of arrays) of scaling parameters that are used in the training phase to normalize and scale down the data set in the margin between 0.25 and 0.75 (refer to Section 4.2).
- Getter functions: for each feature (i.e. inverse eigen vectors for the cluster), there is a *getter* function that returns corresponding feature of the specific subcluster, based on input variables: measuring point ID, cluster number and subcluster number.

Beside described *.h* file, all scripts store their results in specific $.MAT$ files that can be later on reloaded, or further manipulated by others, such as *Matlab*. The structure of $.MAT$ files is similar, but rather each measuring points poses its own $.MAT$ file with its naming, i.e. $Runnable93.mat$. The benefit lays in the ground that, in case of a single measuring points needs retraining, it can be done separately, while afterwards the previously described *.h* file is generated out of $.MAT$ files.
By this, the algorithm workflow from Figure 5.7 is finalized. Next step is to describe Offline

and Online validation process.

5.3 Offline Validation

Before running the online implementation of the algorithm, *AutoSec* needs to be verified in post-runtime evaluations. Firstly, no anomalies will be injected, thus initial testings are to evaluate the number of false alarms and to find the threshold when the number of false alarms starts to increase rapidly.
The trace is recorded with the System (code) running without any anomalies being injected. The following step was to test the algorithm against the data points from the trace. These data points are considered as a test data points, using the notation of standard Machine Learning pipeline. Afterwards the algorithm iterates through these points and calculates the distance d from the test data point to the middle point of the closest cluster found in the neighborhood. The distance d is calculated as Euclidean distance in 3D space:

$$d_i = \sqrt{(x_i - x_0)^2 + (y_i - y_0)^2 + (z_i - z_0)^2}, i \in \{1..N\} \tag{5.1}$$

In the Eq. 5.1, N is the number of data points in the data set, and i is the current data point. Values (x_0, y_0, z_0) are coordinates of the closest cluster. The corresponding distance to the cluster is d_i. Next step is to calculate the distance of a data point to the boundary (sphere) of the closest cluster. It will be calculated as the ratio of distance d_i over the radius of the closest cluster in the direction of the data point. The radius is calculated using the following equation:

$$\rho = \frac{abc}{\sqrt{(ab)^2 \cos^2\phi + (ac)^2(\cos\theta \sin\phi)^2 + (bc)^2(\cos\theta \sin\phi)^2}} \tag{5.2}$$

The values a, b and c are 3 radii that define and explain an ellipsoid (ellipse in 3D space). Angles θ and ϕ are spherical angular of the ellipsoid. Meaning that angle ϕ is polar angle in Oxy plane in local coordinate system of a cluster as depicted in the Figure 5.14. In addition, an angle θ is an azimuth angle in Oz plane as depicted in the same Figure 5.14.

Final step was to calculate the defined ratio of the distance d_i and radius ρ of the cluster in the direction of the data point - Eq. 5.3.

$$ratio = \frac{d_i}{\rho} \tag{5.3}$$

When the ratio has been calculated it is stored in an array of ratios for all N data points in the test data set. Ratios are sorted in ascending order and being presented in the Figure 5.15.

[4]Image source: *Polar angles*

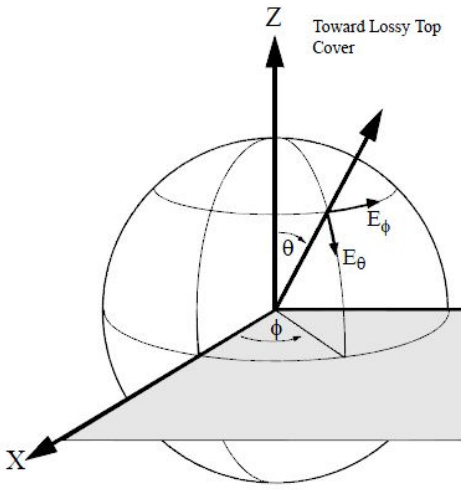


Figure 5.14: Example of spherical angular [4]

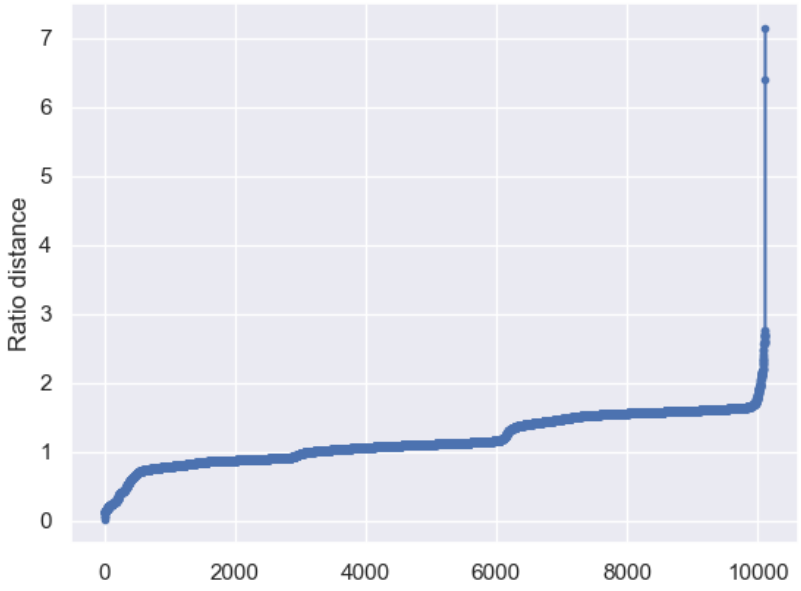


Figure 5.15: Example of distance to the closest cluster

The distances' ratios are presented in the y-axis in the Figure.
Taking a closer look into values and in the Figure 5.15, it can be observed that around 50% of test data points are within the closest cluster boundaries. Furthermore, more than 99% of data points are within double the radius of the cluster. At the end close to all test data points are within the distance under the 3 times the radius of the cluster.
Many figures as Figure 5.15 are examined for different measuring points and data sets of different lengths, the conclusion is reached that the False Alarms are would be close to none, if the threshold to report the anomaly is drawn at the distance of 3 times the radius of the cluster in the direction of the point relative to the center point of the cluster. By taking further analysis, three different threshold can be set:

- WEAK anomaly: ratios between 2.5 and 3
- MEDIUM anomaly: ratios between 3 and 4
- STRONG anomaly: ratios higher than 4

Within the thesis, this element has not been explicitly implemented, but rather used only as a suggestion for the real-world implementation. Throughout further work the threshold was 2.5 as the highest sensitivity to potential anomalies, while being sensitive to False Alarms too. When it comes to evaluation of the anomalistic trace, as mentioned in the previous Chapter, the anomalies are injected in every 50^{th} instance of the measuring point execution. Thus, the evaluation of false alarms and detected anomalies can be successfully evaluated. More about the evaluation in the following Chapter 6 - Evaluation.

5.4 Online System

Following the implementation of *AutoSec* in offline mode using *Python* and verifying the test results, next step was to do the online testing and evaluation of the algorithm in runtime. The algorithm is translated from *Python* implementation into *C* code. For such reasons additional variables are used so to be accessible and trace by debugger in any time during the code execution. Thus additional variables of *volatile* type are used. For debugging purposes and gaining an insight into the algorithm precision in online implementation, additional arrays are used, in order to store the calculation results if the anomalistic behavior has been detected.
Due to proprietary elements in the software that are under Vector Informatik GmbH possession, the implementation itself cannot be revealed here. However, the logic behind the implementation will be discussed. As discussed in previous Chapters, three main different levels of tracing can be distinguished: Task Level, Event Level, Runnable Level. Thus, first step is to instrument elements at the beginning and at the end of the measuring point to gather the timings when the code execution has reached those measuring points.
As previously said, the volatile variables accessed by the debugger are used to mark the point when the new entity (Task/Event/Runnable) has started its execution. When the debugger notice the change in the variable value, the debugger will mark the change with the timestamp using its own clock speed and its own internal timing. Since the Master thesis is prototypical

implementation, this measuring points used by the debugger for tracing are maintained also during an online implementation of the algorithm. The debugger timing readings are maintained for debugging and verification of the online algorithm implementation and calculations. Since the debugger timings cannot be used in the online calculations, the local MCU clock is used to measure online timings. The structure of timings is presented by pseudo-code Algorithm 1. The debugger reads new entity being ran using the variable $isystem\_measuringPoint$. When the debugger, as mentioned, detects the value change in the variable, it reads its own local time as the timestamp. Contrary to that, the online algorithm reads the time from the MCU $timestamp = GetMCUTime()$. The function $GetMCUTime$ reads the internal clock value of the MCU. The clock value is determined using counter that is reset when it reaches maximum value and then starts counting from 0 again. Thus, new offset needs to be set whenever the counter is reseted. The offset is incremented everytime this happens. The incrementation of the offset has the value of the maximum counter value.
Following reading time on the MCU, the debugger will be notified about context change through out the variable $isystem\_measuringPoint$. Only afterwards, the measuring points will be notified about the context change using the previously recorded time. The order of execution is due to minimizing time indifference between time read by MCU and time when the debugger has been notified. However, very important remark follows.
By the end of the Master Thesis, it is noticed that time read by MCU and by the debugger tend to have certain indifference that is not constant. This indifference will be explained later in conclusion for the further work. Many different reasons might be the cause of a behavior. Potential cause is the overhead in the debugger, by debugger: accessing and reading the variable, reading its local time, processing the data, etc.
Regarding the other functions *start, finish, preempt, continue*, a brief overview will be given. Each measuring point is created as an structure consisting of following elements:

- StartTimes[2] (*array of floats*);
- StartToStart (*float*);
- computationTime (*float*);
- numberOfPreemptions (*int*);
- durationOfPreemptions (*float*);
- checkpoint (*float*);

When *start(...)* function is called, a measuring point inserts the *timestamp* value in the array of StartTimes. The first value in the StartTime array is a start time of the previous instance, while the second value in the array corresponds to the start time of the currently running instance of the measuring point. The $StartToStart$ value is calculated as the difference between these two values: $StartToStart = StartTimes[1] - StartTimes[0]$. Other values of computation time, number of preemptions and duration of preemptions have been reset to 0 value. The checkpoint value is initialized to the *timestamp* value. Checkpoint is used for calculating mid-calculation values when a measuring point is preempted, as it is explained

further as follows.
When *preempt(...)* function is called, a currently running (up to that point) measuring point, computation time of the last running leg of the measuring point is calculated by subtracting the *checkpoint* value from the current *timestamp* value. The calculated value corresponds to the computation time of the last running leg and this value will be added to $computationTime$. The value of $numberOfPreemptions$ will be incremented and finally the *checkpoint* will be set to *timestamp* value.
Upon the return to the execution of the measuring point previously being preempted, the $continue(...)$ function is called. Similarly to $preempt(...)$, the difference in times between *checkpoint* and *timestamp* is calculated. At this point, this time indifference corresponds to the duration of preemption of the last preemption leg. The value is added to $durationOfPreemptions$. Again, *checkpoint* value is changed to the *timestamp* value.
Finally, at the end of the execution of the measuring point, $finish(...)$ will be called. Similarly to previous calculations, the last running leg will calculated as the difference between *timestamp* and *checkpoint* value and it will be added to $computationTime$.
At the current implementation status used in the evaluation phase, every $finish(...)$ function is followed by the algorithm of anomaly detection to evaluate last instance of the measuring point. The implementation of the algorithm is explained in previous Sections. The pseudo-code of *AutoSec* is given by Algorithm 2

Algorithm 1 Reading time and creating timestamps

```
Context switch detected
if newEntity == measuringPoint_type then
    if currentMeasuringPoint == None then
        // COMMENT: there is no measuring points executing
        timestamp = GetMCUTime();
        isystem_measuringPoint = newMeasuringPoint « 8 + 0x0F && flag_START;
        start(newMeasuringPoint, timestamp);
        // measuring Point entity is being executed in-here
        isystem_measuringPoint = newMeasuringPoint « 8 + 0x0F && flag_END;
        timestamp = GetMCUTime();
        finish(newMeasuringPoint, timestamp);
    else
        if currentMeasuringPoint.status == Running then
            // COMMENT: Current measuring point is being preempted by a new measuring
            point start
            timestamp = GetMCUTime();
            isystem_measuringPoint = newMeasuringPoint « 8 + 0x0F && flag_START;
            preempt(currentMeasuringPoint, newMeasuringPoint, timestamp);
            // measuring Point entity is being executed in-here
            isystem_measuringPoint = newMeasuringPoint « 8 + 0x0F && flag_END;
            timestamp = GetMCUTime();
            continue(currentMeasuringPoint, newMeasuringPoint, timestamp);
        else
            // COMMENT: Current measuring point is already preempted by an entity that
            has not been traced
            timestamp = GetMCUTime();
            isystem_measuringPoint = newMeasuringPoint « 8 + 0x0F && flag_START;
            start(newMeasuringPoint, timestamp);
            // measuring Point entity is being executed in-here
            isystem_measuringPoint = newMeasuringPoint « 8 + 0x0F && flag_END;
            timestamp = GetMCUTime();
            finish(newMeasuringPoint, timestamp);
        end if
    end if
else
    if currentMeasuringPoint.status == Running then
        // COMMENT: Current measuring point is being preempted by a non-measuring point
        timestamp = GetMCUTime();
        isystem_measuringPoint = newEntity.ID « 8 + 0x0F && flag_START;
        preempt(currentMeasuringPoint, newEntity.ID, timestamp);
        // do something
        isystem_measuringPoint = newEntity.ID « 8 + 0x0F && flag_END;
        timestamp = GetMCUTime();
        continue(currentMeasuringPoint, newEntity.ID, timestamp);
    end if
end if
```

Algorithm 2 AutoSec

```
new_points = scaleDown(input); // input_transformed
new_points = PCA(new_points);
for cluster_ID in set of Clusters do
    Subclusters = loadClusterValues(cluster_ID);
    for subcluster_ID in set of Subclusters do
        // load middle points, radii, eigen vectors and inverse eigen vectors
        subcluster_parameters = loadSubclusterValues(subcluster_ID);
        local_point = transformToLocalCoordinateSystem(new_point,subcluster_parameters);
        angles = calculateAngles(local_point, subcluster_parameters);
        distance = calculateDistance(local_point, subcluster_parameters);
        rho = calculateRho(local_point, subcluster_parameters, angles);
        ratio = calculateRati(rho, distance);
        if ratio > 1 then
            calculated_ratios.append(ratio);
        else
            return CORRECT;
        end if
    end for
end for
ratio = findMinimumRatio(calculated_ratios);
anomalyType = checkAnomalyType(ratio);
if anomalyType == 'WEAK' then
    return WEAK;
else
    if anomalyType == 'MIDDLE' then
        return MIDDLE;
    else
        return STRONG;
    end if
end if
```

Chapter 6

Performance Evaluation

The evaluation of an algorithm or a method depends on what is the target of research and goal to be achieved. Basic requirements are related to the hardware architecture for which the algorithm is developed. Thus, requirements related to the working environment are:

- ***calculation time*** in range of tenths of microseconds - due to high number of potential measuring points (more than ten thousands in some cases)
- ***low overhead*** - due to program execution on the MCU

In addition to that, there are qualitative requirements commonly used in an evaluation of Machine Learning algorithms. Thus, the main requirements for a problem stated by the Thesis are:

- ***Low False Positive Rat***e - reference value $1e-4$ by [9]
- ***High Recall*** - reference values 75% for HIDS by [9], or 81% for NIDS by [26]
- ***High Precision***

The meaning of False Positive, Recall and Precision, and other measures used for Machine Learning algorithm evaluation, will be explained in the following Section 6.1.

6.1 Evaluation Parameters

In order to evaluate the outcomes of Classification method, such as the outcome of *AutoSec*, a confusion matrix is commonly used. The confusion matrix represents a matrix $n \times n$, representing a cross section of classification results, as depicted in the Figure 6.1. On the diagonal it is represented how many elements are classified correctly, i.e. element of a class type A has been successfully classified in 85% as a type A. However, it was misplaced in 15% of cases, out which it was misplaced with type B in 10% and 5% misplaced by type C.

In case of ours, there are two types of classes - *Normal* and *Anomaly*. Thus, the confusion matrix has a size 2×2. The confusion matrix in case of outliers/anomalies detection is given in Figure 6.2. In case of confusion matrix for outliers/anomalies, fields have specific naming,

Confusion Matrix	A	B	C
A	85	20	15
B	5	110	5
C	13	14	93

Figure 6.1: Example of a Confusion Matrix

Confusion Matrix	Correct	Anomaly
Correct	True Negative	False Positive
Anomaly	False Negative	True Positive

Figure 6.2: Confusion Matrix for Outlier/Anomaly Detection

as follows:

- **True Negative (TN)** - *Normal* is detected successfully
- **True Positive (TP)** - *Anomaly* is detected successfully
- **False Positive (FP)** - *Anomaly* is NOT detected; known as ***Type Error I***
- **False Negative (FN)** - *Normal* is detected as *Anomaly*; known as ***Type Error II***

Depending on the application for which the method is developed, ones tend to minimize False Positives (False Alarms), others tend to minimize False Negatives. In the case of HIDS, the requirement stated that False Positives needs to be minimized, while achieving reasonable True Positive value (i.e. higher than 50%). The reasoning behind the requirement is not to warn the driver with potential security breaches unless the system is highly certain that the breach took place. The outcome will be seemingly lower level of True Positives and thus higher level of False Negatives, meaning that quite number of anomalies will pass the system undetected. Although, some anomalistic behavior can be passed undetected, still there are others that would trigger the alarm. In automotive industry, the important element is not to overflow a driver with the information unless it can be with high certainty classified as highly important and relevant information to be delivered to the driver. However, apart from Type Error I and II (False Positive and False Negative, respectively), there are other additional measures to evaluate the outlier detection algorithm.
When it comes to the evaluation of detecting outliers, as anomalies in the case of *AutoSec*, it is not often an easy task. The reason is described in-depth by [40]. The drawback in detecting

outliers, or anomalies, and evaluating an algorithm to detect so, is lack of ground-truth, meaning no labels of outliers and anomalies are available. Following paragraph is quoted from [40]:
"In outlier detection, a more reasonable (albeit imperfect) approach is to use external validity measures. In some cases, the data sets may be adapted from imbalanced classification problems, and the rare labels may be used as surrogates for the ground-truth outliers. In such cases, a natural question arises as to how the ground-truth can be used to evaluate effectiveness. Most outlier-detection algorithms output an outlier score, and a threshold on this score is used to convert the scores into outlier labels. If the threshold is selected too restrictively to minimize the number of declared outliers, then the algorithm will miss true outlier points (false negatives). On the other hand, if the algorithm declares too many data points as outliers, then it will lead to too many false positives. This trade-off can be measured in terms of precision and recall, which are commonly used for measuring the effectiveness of set-based retrieval."
Precision is defined by Eq. 6.1. The *Precision* gives the result of how many true anomalies have been detected out of all reported cases. An example for $Precision = 95\%$ means that out of 100 reported cases (outliers), 95 of them are true anomalies, whilst other 5 cases are normal behaviors reported as outliers.

$$Precision = \frac{TP}{TP + FP} \tag{6.1}$$

Recall is defined by Eq. 6.2. The result of *Recall* shows the capability of an examined method, i.e. how many anomalies out of all known anomalies have been successfully detected. Thus, the $Recall = 80\%$ means that 80/100 anomalies are detected, the other 20 anomalies passed undetected, below the set threshold. The other name for *Recall* is also True Positive Rate (TPR).

$$Recall = \frac{TP}{TP + FN} \tag{6.2}$$

FPR, defined by Eq. 6.3, is, contrary to TPR, a ratio how many instances of normal behaviors surpassed the threshold and have been reported as outliers.

$$FPR = \frac{FP}{FP + TN} \tag{6.3}$$

By defining these values, outcomes of those will be used to evaluate the achievement of *AutoSec* and fulfilment of set requirements. The algorithms to be used head-to-head are *AutoSec* and [9] used as HIDS. In the paper [9], the tests were run on two different threshold levels - *lower* and *higher* sensitivity level. The achievements presented in [9] were:

- **FPR**

  $FPR_{lower} = 0.6897\%$

$FPR_{higher} = 0.098\%$

- **Precision**

  $Precision_{lower} = 98.54\%$

  $Precision_{higher} = 99.89\%$

- **Recall**

  $Recall_{lower} = 88.43\%$

  $Recall_{higher} = 45.12\%$

Since the paper implemented their proposed algorithm (*SecureCore*) onto different hardware architecture, the specific implementation of the same algorithm in AUTOSAR due to time limitation was not directly implemented. The results presented in the paper [40] are used as such as a trend setter.

6.2 False Positive Rate (FPR)

First evaluation step is to evaluate how many false alarms, algorithm tends to report. By doing this, the threshold is set to satisfy requirements. Since the requirements in case of the Thesis is to minimize the FPR, threshold will be set higher by reducing the *Recall*. Trade off of this can be discussed upon Figure 5.15 from the previous Chapter 5 - Section 5.3. In the Figure can be observed that threshold for ratio value shall be placed between value 2 and 3. Thus, the *"fuzzy"* anomaly level should be used, as discussed in Chapter 5 - Section 5.3: *WEAK*, *MEDIUM* and *STRONG* anomaly. Thus, for simplicity reasons a hard threshold was taken for all measuring points. The threshold values depends highly on the measuring points, i.e. in the Figure 5.15 a value 2 could be taken as a threshold, whilst for some other measuring point it could be value 3. In order to avoid this dependencies, and to have a hard threshold as used in [40], a single threshold value will be used: $threshold = 2.5$. By doing this, a results would be than rather pessimistic and it will downgrade the *Precision* and *Recall* results. Therefore, the important remark announces that for real-world applications in industrial production shall take evaluation on each measuring points and set thresholds accordingly.
The Thesis has run the evaluation with fixed threshold of 2.5 for measuring point on the Runnable Level and on the Event Level corresponding to higher and lower sensitivity levels, similarly to sensitivity levels evaluated in [40]. The evaluation is run on the program allegedly without any anomalies present in it. In later evaluation of IDS, FPR will be reevaluated under circumstances that there were actual anomalies being injected.
Since some Runnables are triggered upon received data through CAN communication, this can shift the order of execution of other Runnables. In order to include such elements into the evaluation of FPR, the program will start with the execution and later in time, CAN communication will start sending data: i.e. there will be no CAN communication and it will

start at $t = 10s$ and virtual ECUs will keep sending data to real ECU (evaluation board with MCU running the code) for some time and then stop sending data. By this, different "*ECU states*" will be changed. The length of trace used for evaluating FPR was 300 seconds or 5 minutes. Evaluation was run on periodic and aperiodic Runnables, and periodic Event. Regarding aperiodic Runnable, its function was to process incoming CAN messages from a virtual ECU that was sending values from sensors. Sensor inputs are simulated using inputs to CANoe. The frequency of sensor readings was 5ms, so the aperiodic Runnable under the test should behave as a periodic Runnable since it depends on the input that has a periodic behavior.
The results of the evaluation on different levels are as follows:

- $PeriodicRunnable : FPR_{lower} = 0.0000\%$
- $AperiodicRunnable : FPR_{lower} = 0.0000\%$
- $PeriodicEvent : FPR_{higher} = 0.0067\%$

The results of FPR evaluation are on a margin of error, since there were no outliers being reported on Runnable, more sensitive level to deviations. For periodic Runnable no false alarms were raised on 30041 instances, as well as, no false alarms being raised on 64896 instances of aperiodic Runnable. However, on more robust level with higher threshold of sensitivity, on Event level, there were 2 outliers being reported out of 30051 instances, resulting in FPR on Event level being 0.006655353%.
The reasoning behind this values can be explained by influences from entities that were not instrumented by measuring points. One of the examples is given in the following Figure 6.3 - it presents the execution of the consecutive instances of the same Task->Event consisting out of 5 Runnables, meaning that all 5 Runnables belong to the same Event in the same Task. The period of the Event that encapsulate the execution of these 5 Runnables is 10ms. Since Runnables are executed consecutively, they are supposed to have Start-to-Start value of 10ms. The Runnable is marked with dark blue color when it is *running* and with pale blue color for the time when it is *preempted*. The trace in the figure was supposed to be normal. Only Runnable 5 was instrumented as a measuring points.
The normal (common) execution learned by *AutoSec* looks like the first instance of Runnables' executions (left part of the Figure 6.3) - short consecutive executions of Runnables without preemptions. Suddenly, during the execution of the following instance (right part of the Figure 6.3), Runnable 4 happened to be preempted multiple times with long preemptions that pushed the start of execution of Runnable 5 later in time. Thus, for the second instance of Runnable 5, depicted in Figure 6.3), resulted in deviation in feature spaces reporting it anomalistic behavior. Although the report states instance has an anomaly, the reason does not necessarily lays in the measuring point itself, but it could be invoked by anomalistic behavior of some prior entity that was not instrumented.
Since the Start time of the second instance was later in time and thus has a longer Start-to-Start time, this will result in reporting the anomaly in the third instance as well. The reason for such behavior is following: if the period of 10ms is honored and assuming that the execution of next consecutive runs of Runnables 1 to 5 will start on time, this will result in third instance having shorter Start-to-Start time, because second instance previously started

later in time. This is not necessarily the case, but it might happen. By this, instances of the same measuring point have higher connection dependency and increased the chance of detecting the anomaly. The example from Figure 6.3) originates from one of traces used for training, where the behavior of Runnable 5 from the Figure reported it anomaly within the training dataset that was supposed to be anomaly-free.

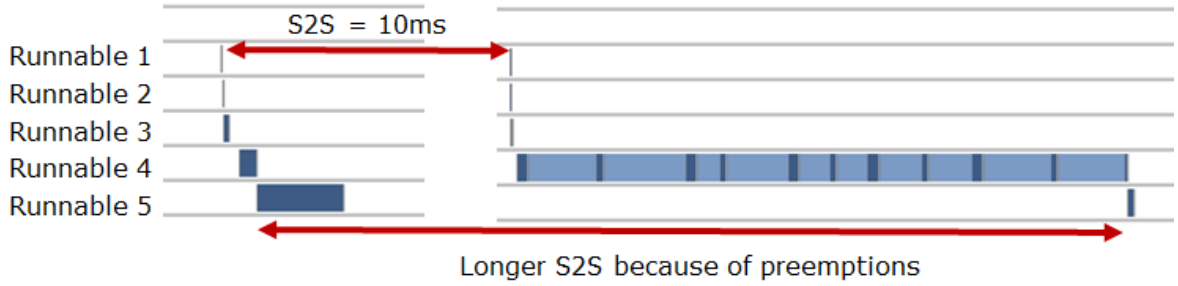


Figure 6.3: Anomaly in Runnable 4 detected by Runnable 5

By summing up the FPR evaluation on assumingly no anomalies being present in the trace, it can be said that using a threshold of 2.5 satisfies the requirements of minimizing the FPR on the execution of no anomalies being detected. Next step was to inject anomalies and rerun the algorithm to evaluate results on known anomalies being present in the execution of the program running on the ECU.

6.3 Injecting Anomalies

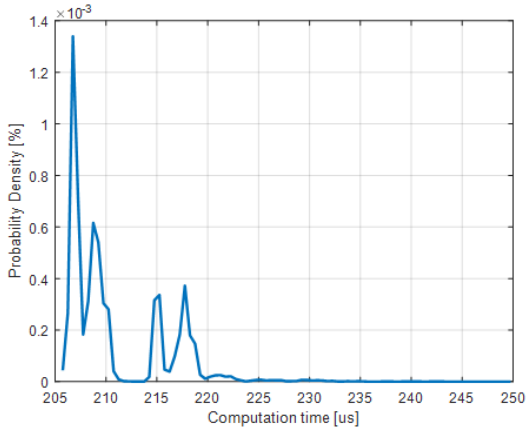
After evaluating algorithm under normal circumstances, next step was to insert anomalies and invoke the algorithm to detect them. In addition to FPR, the algorithm was put under the evaluation for*Precision* and *Recall*. Considering that no attack model is used as a baseline, anomalies to be injected would manipulate *S2S* and *Computation Time* of a measuring point. When it comes to preemptions, it can not be easily manipulated with high certainty of external triggers.
A situation how an attacker gains an access to the code is not part of the Thesis. Furthermore, following gained access, the attacker would insert its malicious code. Multiple possibilities could result in the behavioral outcome of the malicious code, depending in which part of the code it was injected. The behavior could result in different types of anomalies in terms of timings used as features:

- *Computation Time*
    1. Shorter
    2. Longer

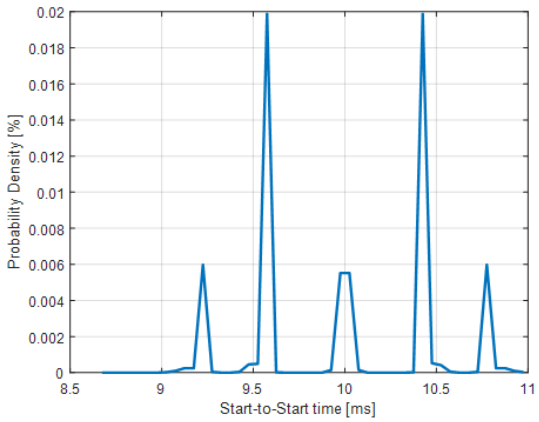
- *Start-to-Start*
    1. Earlier start
    2. Later start
    3. Omission - scheduled instance to be skipped
    4. Commission - additional instance aside scheduled once to be executed
- *Number of Preemptions*
    1. Too many
- *Length of Preemptions*
    1. Long
    2. Short

Computation time and Start-to-Start will be manipulated during the evaluation phase of *AutoSec*. When it comes to Computation time, the attacker could have injected the code within the Entity instrumented by measuring points. This could result in longer execution time of the Entity. Contrary, the attacker could have overridden, or bypassed the original code of the Entity, so only its code would be running. This could result in shorter computation times. These different behaviors will be used to inject anomalies.
Computation Time anomalies are injected within measuring points of the Entity. Anomalistic code runs some calculations and writes results in the array in order to have memory dependencies included in the code that is anomaly - simulating data sniffing by anomalistic code. The length of execution of the anomaly will increase over time in order to evaluate the algorithm sensitivity on different lengths of anomalies by sweaping through out probability density function, example given in Figure 6.4a. Thus, first 10 instances would introduce 1% longer computation time, following 10 instances would introduce 2% longer computation time, etc. **Start-to-Start Time** anomalies are injected by same reasoning as by *Computation Time* anomalies. In a case of Start-to-Start Time manipulations, the idea is to simulate anomalistic code executing outside the measuring points. However, the sensitivity to these types anomalies highly depends on average deviation of normal execution of the measuring point. By Computation Time, deviation in range of 1%, from mean execution, was approximately 2-3 microseconds. Yet, by Start-to-Start Time, in a case of measuring point with the period of 10ms, deviation in range of 2-3microseconds used for Computation time, equals deviation of only 0.2% from the period - Figure 6.4b. Nonetheless, the Probability Density Function displayed in the Figure 6.4b can be defined using 5 Gaussian distributions. Examining the width of each peak in the Figure 6.4b, it can be seen that it is in range around 100 microseconds - (1%) deviation from the period. In a case of the example from the Figure 6.4b, the Gaussian distributions are rather wide with steep edges, making deviations of a few microseconds within range of high probability for normal execution. Thus, the Start-to-Start manipulation will be executed with the anomaly in range from 1%, 2%, etc. from the period

(mean S2S value).
The results of Computation Time and Start-to-Start time manipulations listed previously will be presented in the following Section.



(a) Computation Time Probability Density Function



(b) Start-to-Start Probability Density Function

Figure 6.4: Probability Density Function

6.4 Results

The results of evaluations will be divided into parts - firstly S2S will be discussed followed by discussion on for Computation time results. The structure of evaluation follows firstly Event Level evaluation for increasing deviations. Anomalies are triggered in every 50^{th} instance of the Entity under the supervision. Furthermore, the anomaly will have the same deviation for 10 consecutive anomalies, afterwards the deviation will increase and then following 10 consecutive anomalies will have new deviation, and so on.
Regarding S2S, there are additional tests: *Omission* and *Commission*. The results for these two types of anomalies resulted in those being detected in every single case. Thus, additional executions, or blocked executions of the Entity will be 100% detected. Furthermore, regarding anomalies that influence earlier or later start as small deviations of S2S resulted in following outcomes - see Table 6.1. Values are average values over 6 different test cases for Runnable level and 3 different test cases for Event level.

By reading results, it can be concluded that for smaller deviations, the *Recall* was below 40%. Although results on *Recall* shows the algorithm is not sensitive for small deviations, the requirement regarding FPR resulted in low level of False Alarms in range around 0.01%. Thus, there are 1 false alarm reported on every 10000 instances. However, if a new instance is started every 10ms, the False alarm would be triggered once in a minute or two. The result is rather not sufficiently satisfying for production line in automotive industry, although FPR is below $1e-4$. In order to satisfy strict requirements for production line in automotive

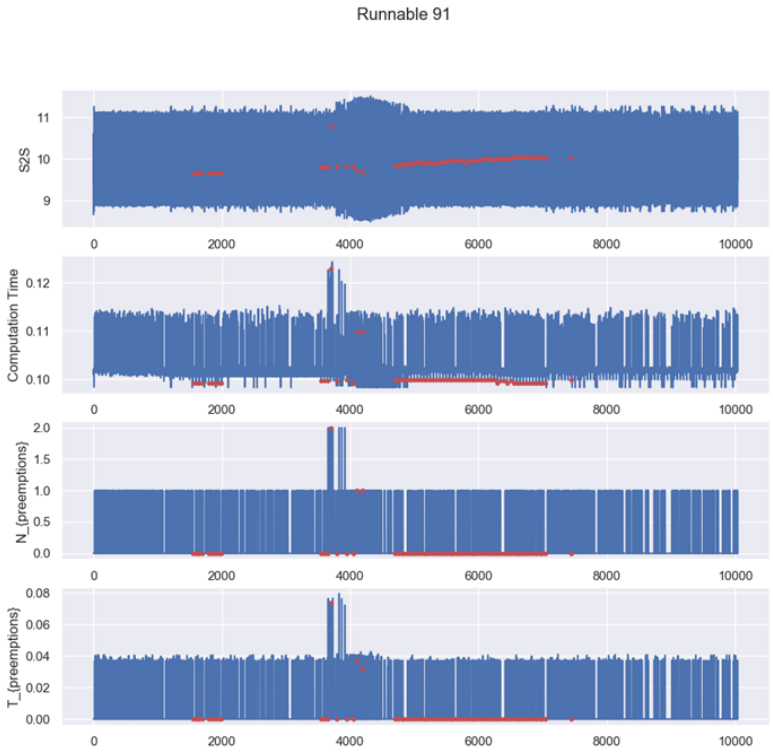
	Runnable Level		Event Level	
S2S Time Anomaly	[1..25%] deviation	[25..40%] deviation	[1..20%] deviation	[25..40%] deviation
FPR	0.00605632%	0.02004812%	0.01976089%	0.01978351%
Recall	33%	79%	34%	64.52268361%
Precision	99%	98.77%	97.18%	98.46047794%

Table 6.1: Results on *FPR*, *Recall* and *Precision* for Start-to-Start-time type of injected anomalies

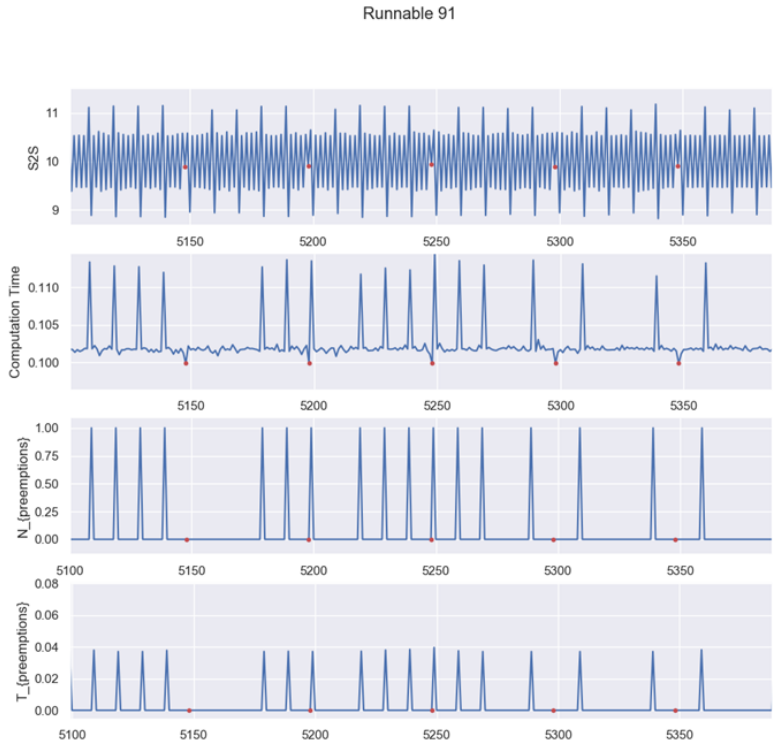
industry - FPR should have been below $1e-19$ that is super extreme value. Thus, additional evaluation shall be included for evaluating reported anomalies based on additional external information that require high overhead in implementation.
Before giving the comparison between obtained result by *AutoSec* and results of the SecureCore from [40], Computation Time will be evaluated. The results of Computation time anomaly injections are presented in Table 6.2. Values are average values over 5 different test cases for Runnable level and 4 different test cases for Event level.

As presented through the Thesis, Runnable level is fine-granule level that is more sensitive to deviation and anomalies in behavior. The results of the evaluation shows that: in case of 5-10% deviation resulted in $Recall_{computation} = 100\%$ for Computation anomalies and $Recall_{S2S} = 79\%$ for S2S anomalies. It is important to say that, in most cases based on deviations on each feature, a hard threshold could be defined, i.e. *if Computation time longer than x or shorter than y value, reported as an anomaly.* These values of "obvious" anomalies beyond easily determined hard threshold were not taken into the consideration, but rather values that are within these boundaries. The best representation is depicted in the Figure 6.5a.
In Figure 6.5a, the change of features' values over time is displayed. By mark dots, anomalistic instances are marked. In Figure 6.5a, on $x-axis$ of each feature is the instance *ID* equal to timeline. On $y-axis$ of each graph is the value corresponding to the feature.

As it can be seen in Figure 6.5a, anomalies (red points) are in between hard thresholds. In case of S2S, hard thresholds would be *longer than 11.5ms* and *shorter than 8.5ms.* By taking a closer look by "*zooming*", the better look is displayed in Figure 6.5b. As it can be seen, instance having an S2S of exactly 10ms value in combination with other features is reported as the anomaly since it does not fit in the normal execution. Anomalies were detected since



(a) Anomalistic instances (marked by red) on each feature over time of traced measuring point



(b) Features over time of traced measuring point [zoomed Figure 6.5a]

Figure 6.5: Anomalistic instances (marked by red) on each feature over time of traced measuring point

	Runnable Level		Event Level	
Computation Time Anomaly	[1..10%] deviation	[5..15%] deviation	[1..10%] deviation	[5..15%] deviation
FPR	0.030305%	0.015%	0.00499%	0.010068%
Recall	76.5%	100%	22%	56.5%
Precision	98.115%	99.26%	98.81%	99.09%

Table 6.2: Results on *FPR*, *Recall* and *Precision* for Computation-time type of injected anomalies

they have been too far from the closest cluster. The result is depicted in Figure 6.6, whereas the axis are now *Principle Component 1* vs. *Principle Component 2* vs. *Principle Component 3* - new feature spaces in 3D space obtained from original 4D timing feature space by PCA. Detected anomalies are presented by black dots, and different cluster with different cluster whose middle point is depicted by black square point. Due to limitation of presenting 3D space as a figure of 2D dimensions, some anomalies seems to be within the cluster, however if we would be able to rotate the picture, it would be seen that it does not belong to any of clusters.

Another interesting example, why combination of different timing features is important is present in Figure 6.7. Taking a look into the exact values of reported anomalies, it can be seen that values for S2S feature are among normal execution. The computation time is in range of occasional longer computation times that are around 110 microseconds. Number of preemptions in cases of anomalies is is *None* and thus the duration of preemptions is equal to zero. Examining each of those features separately shows nothing uncommon or non-ordinary. Nonetheless, overlapping these features, a reason reveals that longer computations in range around 110 microseconds happen in some cases if only a preemption has happened. Since, in the case of anomalies for that long computation time, no preemptions happened, algorithm has detected those instances as an anomalisitc instances.

Results presented in the Table 6.2 and Table 6.1 are average values of all tests that were rather pessimistic and strict on evaluation of *AutoSec* method. Tests were designed in a way that anomaly values are in the range of high probability of timing features. By this approach, it was tested how good *AutoSec* can detect anomalies that appear common by each separate timing, while being an outlier and anomaly when all timing features are combined.

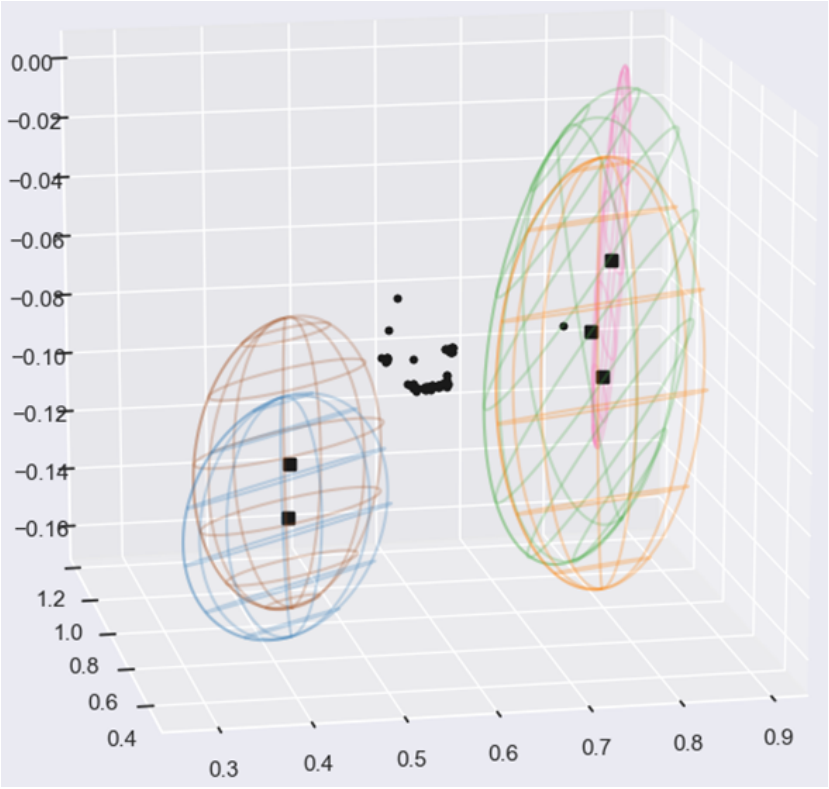


Figure 6.6: Anomalistic instances (marked by black dots) in feature space of measuring point

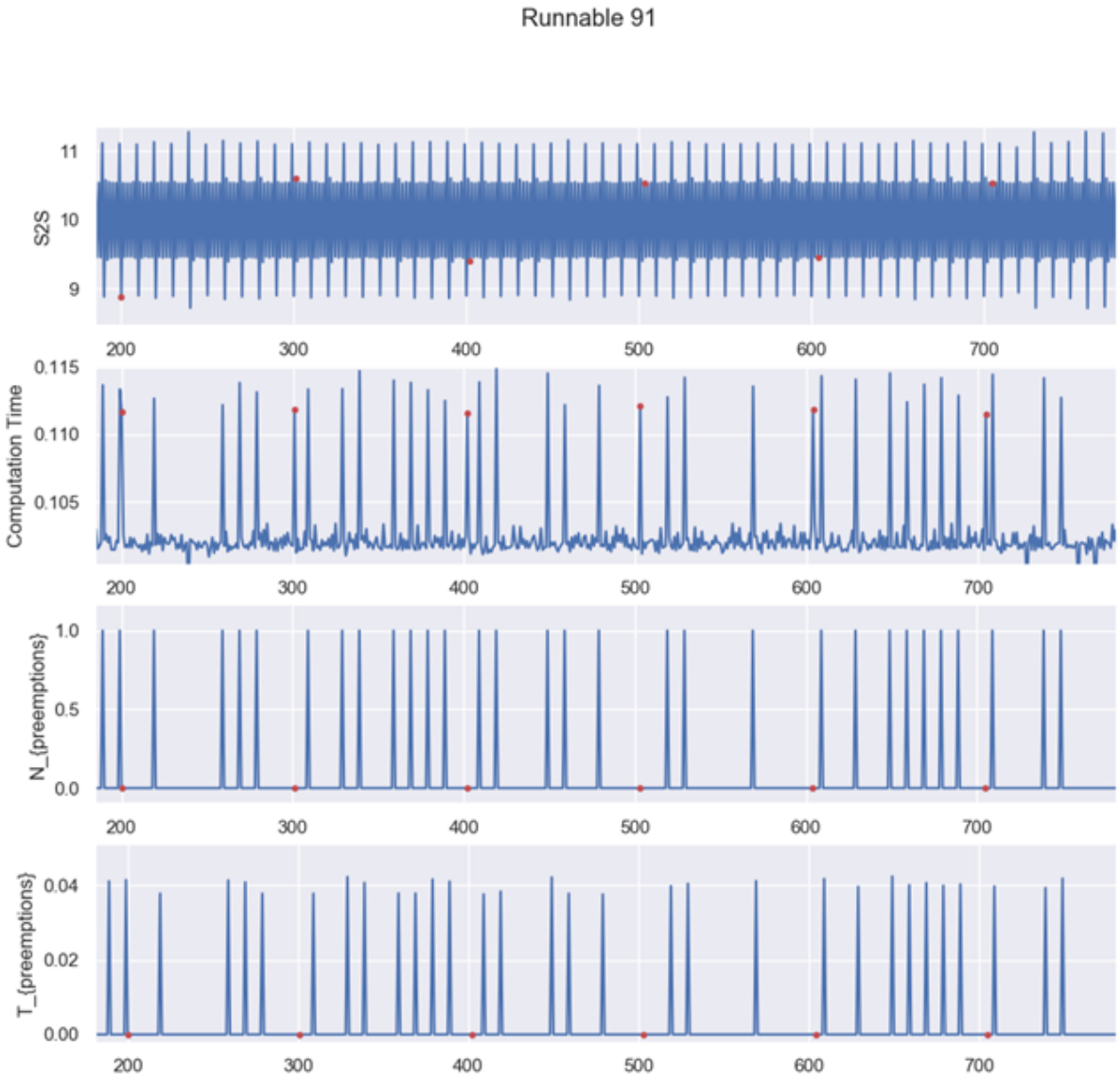


Figure 6.7: Anomalistic instances (marked by red dots) for each feature over time

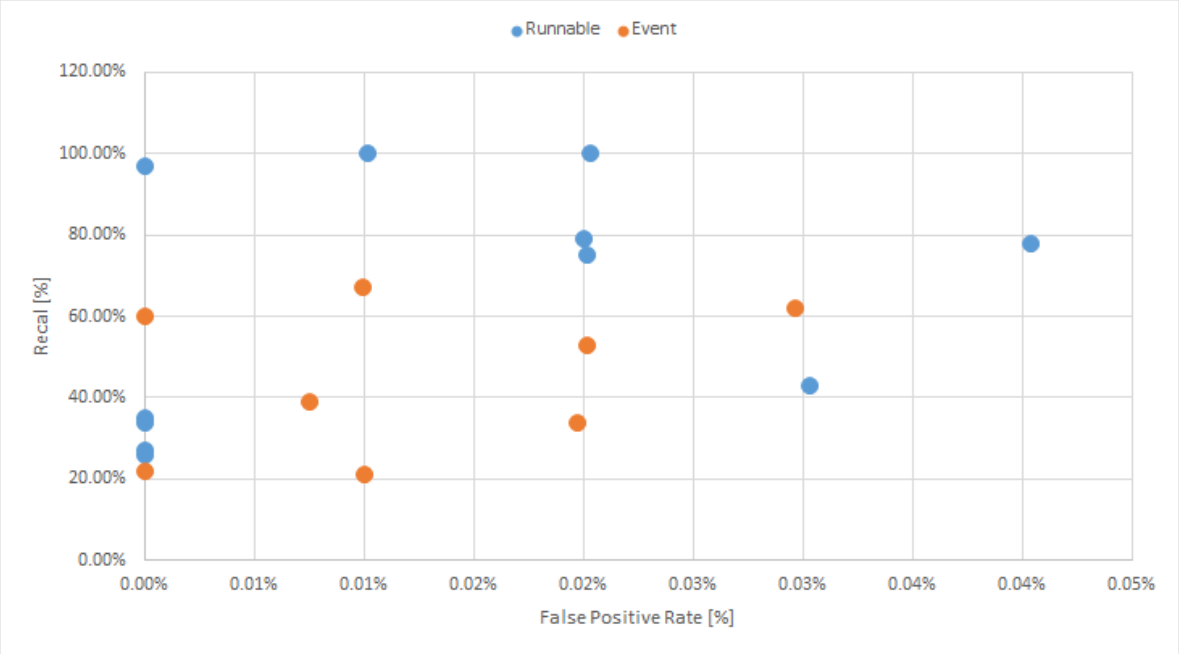


Figure 6.8: FPR vs. Recall - Runnable level vs. Event Level

Tests were designed to test this type of anomalies, whilst the values beyond some hard thresholds could be with high *Recall* and low *FPR* detected by using simple threshold values based on examining Probability Density Function by experts. In following Figures are presented scatter plots of run tests with different time deviation. The conclusion can be drawn on difference of different tracing resolution: Runnable Level vs. Event Level (Figure 6.8). The results on Event Level have lower Recall in comparison to Runnable Level, due to coarse resolution of timings and thus small deviation in a few microseconds within one Runnable traced under the Event could not have been detected as it would be the case if that Runnable was monitored independently and separately. By similar reasoning, if one Runnable is traced, it is more sensitive to computation timings of its own than by deviation of timings from previous Runnable. If previous Runnable has some longer execution time, it should have some higher degree of deviation in order to influence significantly S2S parameter of Runnable under monitoring. The reasoning is behind different magnitude of timings in Computation times and Start-to-Start times since 1% out of $10ms$ and 1% of $200\mu s$ are $100\mu s$ and $2\mu s$, respectively. Therefore the results of Tests on Start-to-Start Anomalies have lower Recall then Computation Anomalies test results, in both cases of Runnabble Level (Figure 6.9) or Event level (Figure 6.10) of monitoring.

Papers listed in Chapter 3 do not list their results under same evaluation values. Some papers have only discussed the results, without providing the exact numbers, while others have evaluated their method using acFPR and Recall, or Recall and Precision, or only one of these 3 parameters. Figure 6.11 demonstrates a comparison between AutoSec and following IDS methods - [cite papers here], which used FPR and Recall as evaluation values. In addi-

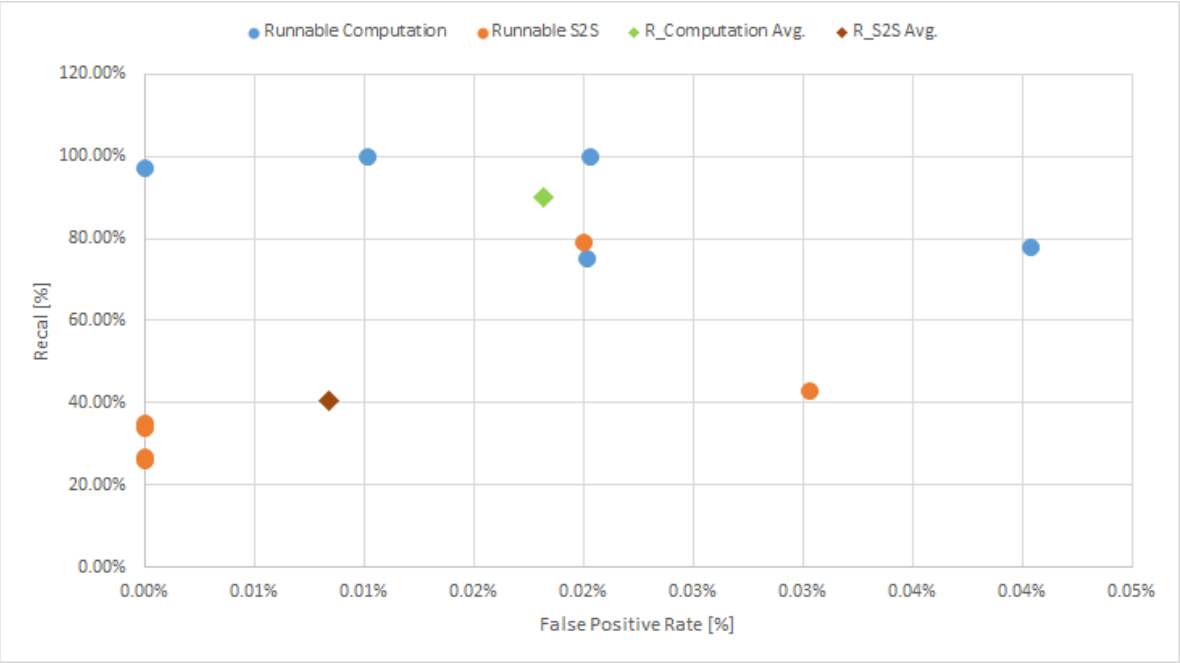


Figure 6.9: Runnable Level: FPR vs. Recall

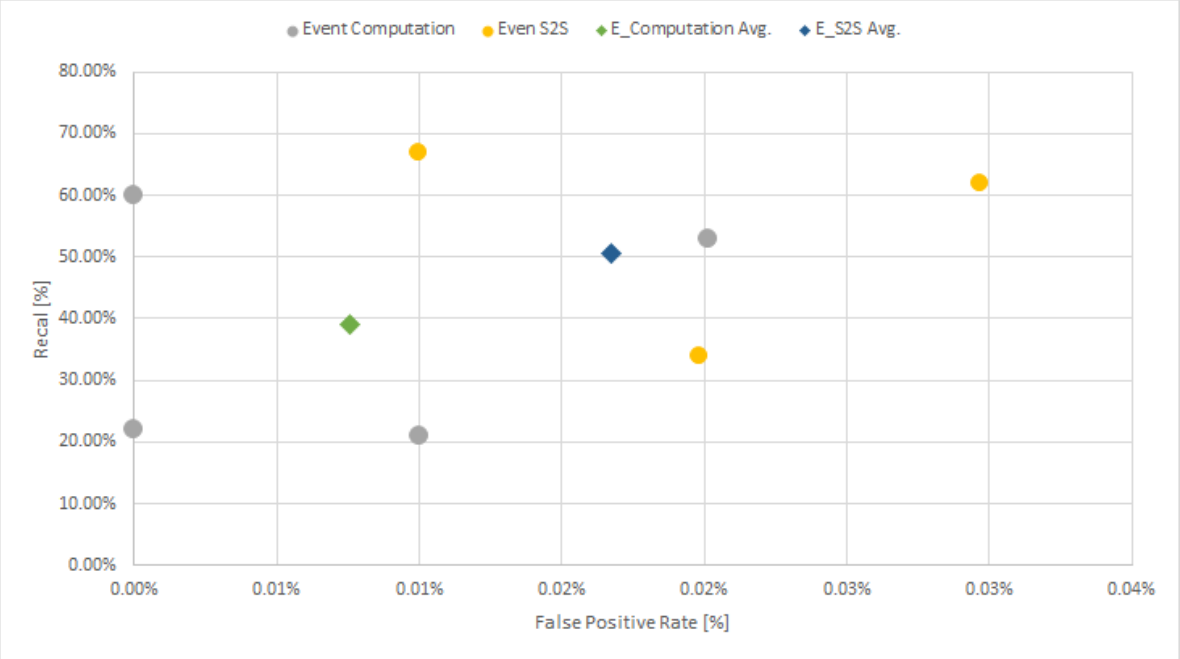


Figure 6.10: Event Level: FPR vs. Recall

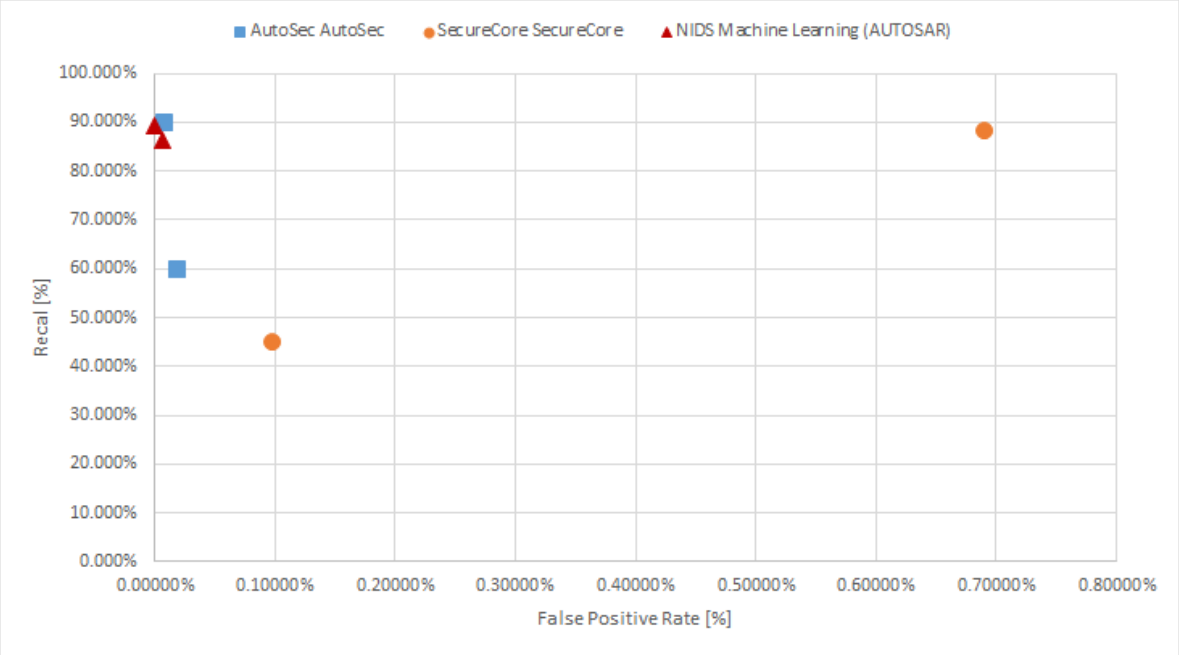


Figure 6.11: FPR vs. Recall - AutoSec vs. others

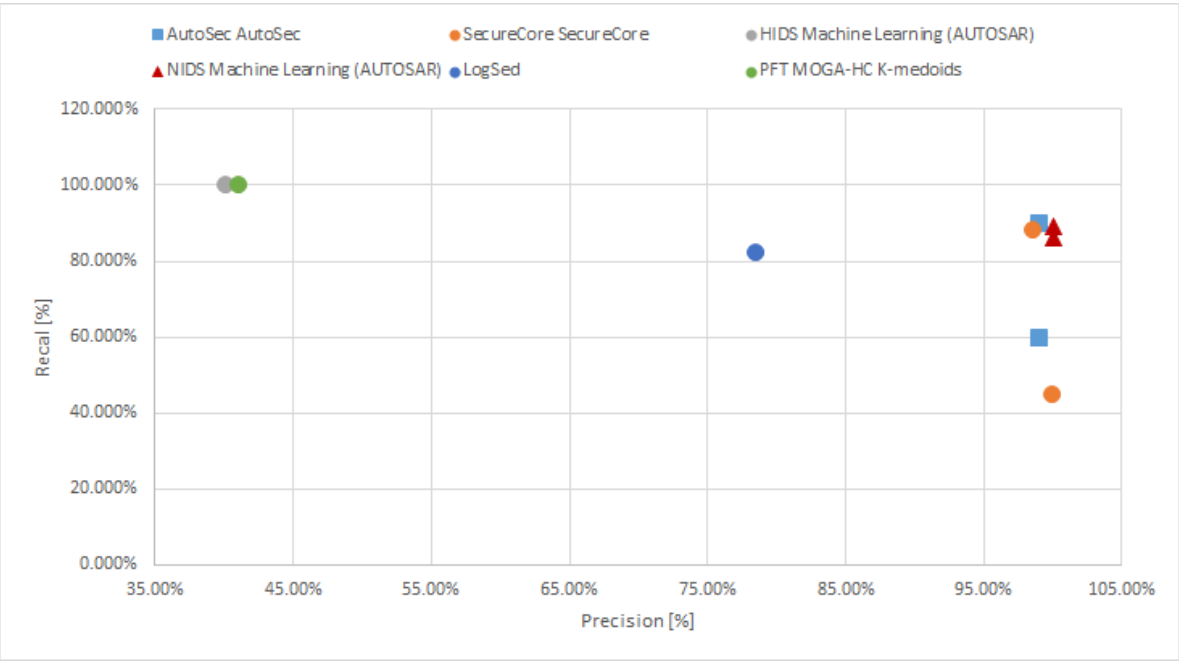


Figure 6.12: Recall vs. Precision - AutoSec vs. others

tion,Figure 6.12 demonstrates a comparison between AutoSec and following IDS methods - [cite papers here], which used Recall and Precision as evaluation values. IDS methods that have been developed for Automotive Industry, mainly for AUTOSAR standard have mark *(AUTOSAR)* in addition to their names. The comparison from Figure 6.11 and Figure 6.12 shows that the AutoSec has outperformed other methods under the requirements:

- FPR - minimize
- Recall - maximaize
- Precision - maximize

The AutoSec has outperformed baseline method SecureCore [9] by 10-50 times in FPR reduction and increased the Recall.
By evaluating algorithm, a conclusion can be reached that the algorithm can successfully detect anomalistic behaviors using multifeature space even. Tradeoff between FPR and *Recall* highly depends on the requirements and results that are wanted to be achieved. More about this topic in the following Chapter 7. Before, reaching the final conclusion. It is important to evaluate the algorithm overhead.
The overhead is mainly measured in time needed to process *AutoSec* algorithm. Although needed processing time is highly dependent on the hardware under which the algorithm will be running, an insight can be drawn. In majority of cases, MCU are used in ECUs. Thus, the clock speed is range of hundreds of MHz. In case of the testbed, the speed of used MCU was 120MHz. The algorithm was running on a single core out of three available cores on the used MCU. The core in use was the core with highest usage, with most Runnables and Events. The reason is due to fact that at current stage of *MICROSAR*, each Runnable is mapped to specific core during a design time and it will not change, during the runtime, the core under which it is being executed. Thus the overhead of code implementation could have been measured using internal clock of the MCU for the core where algorithm was running. The results showed that one run of the algorithm to evaluate instance was in range between 40 and 200 microseconds. The range of execution depends on how many clusters exist for the measuring point under the evaluation and whether the instance is anomalistic or not. For the instance that is anomalistic, algorithm would need to measure the distance of the anomaly, in feature space, to each cluster. Since these calculations take time due to multiple multiplications, divisions and using square root functions, the execution time requires more computation time by MCU introducing overhead. Although 200 microseconds does not seems long, put it in equation that some ECUs can run more than 10000 Runnables, and by instrumenting each as a measuring point, total overhead would be 2s. Thus, such implementation is not feasible. Therefore, a risk assessment on Runnables is needed to evaluate which Runnables should have been instrumented as measuring points due to higher security risk.
Final conclusion on tradeoffs and comparison to the results from [40] will be discussed in the following Chapter 7.

Chapter 7

Conclusion

Automotive industry is highly competitive environment with no room for errors since safety and security are highest priority beyond customers' expectations on comfort of travelling. Vehicles reached high level of complexity and system dependencies that require extensive data exchange through various communication channels and mediums. In addition to standard vehicles features being seen in modern vehicles up-to-day, the interconnectivity of systems will expand beyond the car by networking vehicles among and with the road infrastructure. Thus, points of failure and possible access points for malicious parties and attackers are exponentially increasing. Number of threats to passengers safety and security of the information increases. The turning point that made OEMs and Tier suppliers to pay more attention to security that can influence safety of passengers happened in 2015. [2]. Charlie Miller and Chris Valasek exposed the potential security holes through which an attacker can gain an access to highly risk elements of the car, such as controlling the engine or disabling braking system, etc. Since they have published their breakthrough, the security was made the top priority of all vehicle manufacturers and their developers and suppliers.
The defense against potential attacks on vehicles is fresh field of work with not many known potential attacks. The system complexity and fast development of those leads to not easily detectable potential points of breaches by malicious code or an attack. Thus, the object is to develop an algorithm to detect intrusion in the system, or known as *Intrusion Detection System*. Since the vehicle consists out of more than 100 ECUs interconnected among using different types of communication mediums and protocols, the intrusion can be done in two distinctive ways: through communication or by direct access to an ECU. Therefore, there are two type of intrusion detection systems: *Network-based IDS* and *Host-based IDS*.
Since, the network attacks are already examined by other fields in computer science, attacks by direct access to specifically oriented hardware (embedded systems) were not much researched. Therefore, the scope of the Master Thesis to do a research on what has been done and examine fields of potential use in automotive industry. When it comes to HIDS, in major scope of research and papers was the context of the program. Since, the exact attack is unknown, thus the defense measures against unknown attack is to observe for anomalies in the system. Therefore, some algorithms in this field make a trace on the order of execution of functions and commands within the code. Downside appears in areas if something highly rare, but still normal and verified, happens, can lead to significantly different order of execution and thus making a method to report further normal execution as an attack. Apart from that, this field was researched in most of cases when it comes to HIDS.

Contrary to order of execution and call flow of functions, timings of executions in the system were not commonly researched, best to the author's knowledge. The timing of execution reflects to evaluating duration of execution of a function. The work in this field of tracing execution values was done by [9]. As described in Chapter 6, measures used to evaluate outcomes' score are *FPR*, *Precision* and *Recall*. In [9] achieved values were:

SecureCore	Lower Threshold	Higher Threshold
FPR	0.6897%	**0.098%**
Precision	98.54%	**99.89%**
Recall	**88.43%**	45.12%

Table 7.1: SecureCore evaluation results

TimedCore	Runnable Level	Event Level
FPR	0.018%	**0.0075%**
Precision	99%	**98.95%**
Recall	**90%**	60%

Table 7.2: TimedCore evaluation results

Examining values shown in Table 7.1, it can be seen that FPR needs to be reduced, whilst *Recall* to be increased in case of higher threshold. In order to do so, the method proposed by the Thesis (*AutoSec*) experimented with other timing features: Start times, preemptions and duration of preemptions. The novel approach, best to the author's knowledge, used four different timing features in a single feature space. Feature space is such that each axis in this

space represent a feature axis, i.e. x-axis is computation (execution) time, y-axis is Start-to-Start time, z-axis is number of preemptions and p-axis is duration of preemptions. Examining the distribution of data points collected from tracing assumingly non-anomalistic program execution, distinctive attributes have been noticed. Attributes represent the distribution nature in the feature space. Using additional mathematical manipulations, a final method was developed and presented throughout this Thesis, mainly in Chapter 4, Chapter 5 and Chapter 6. The outcome of algorithms evaluations showed results presented in Table 7.2.
The improvements have been made in direction of decreasing the FPR by factor 10-40, while increasing the *Recall* values up to 15% in case of higher threshold. The results of both methods cannot be easily justified in any case or directly compared head-to-head. The results highly depend on the application and use case. The tradeoff mainly between FPR and *Recall* is on the designer of the system, while fulfilling the requirements on the overhead and response time on anomaly manifest.
The main contribution of the proposed method, *AutoSec*, is that it can be used on any number of measuring points and on different levels of sensitivity, independently on other measuring points in the system. The benefit is on the side that the algorithm is independent on program context since the program block is observed as a black box and examined from the outside on measures - *Timing Features*. In addition, important mark is needed to be said. The results depicted in the Table 7.2 are rather pessimistic in two elements. Values on FPR are in real cases rather lower since in reported False Alarms were not necessarily *False*. The reason is behind the chain reaction of events. An example is similar to Figure 6.3, by introducing an anomaly in one measuring point, it makes an influence also on post entities. The reaction on post entities can backfire to other instances of entity under the observation. Thus, the later instance of the entity under the observation will report an anomaly although none of anomalies have been injected to that specific instance. The report would be classified as a False alarm, although it was realistically influenced by prior injected anomaly. Due to hardship in examining each False alarm whether it is actual false alarm or not, all reported false alarms were classified as False Positives. Therefore, results of FPR are rather pessimistic reflection on the real performance of the algorithm. Thus, the performance of the algorithm shall be considered as better than it is depicted in the Table 7.2.
Every improvements comes with costs in other areas. The overhead of algorithm implementations results in high computation time needed to process the evaluation of instance whether it is anomaly or not. Considering the stage of current requirements and outcomes of the algorithm, the method would be highly beneficial during a design time and evaluation of the design to early detect the potential outbreaks in the system. By doing as such, the overhead of the algorithm would be minor on modern PCs and the tracing could be done with high sensitivity level sacrificing thus increasing level of FPR since FPR does not play high role in offline mode during the design time.
In addition, important remark shall be said on noticed indifference between recorded times in the MCU and by the debugger. The reason is already presented in previous Chapter 6. Tracing times that are used as training data set shall be improved in some future work in order to avoid timing overhead introduced by the debugger and by doing so to improve the precision in calculation in online mode of the algorithm. The online evaluation results show lower values from those presented in the Table 7.2 due to previously mentioned reasons and overheads. Debugging and resolving the issue of overhead and timings mismatches that is an

issue with higher scales to be examined on its own by some future work, and thus it was not further investigated by this Thesis.
Finally, the conclusion can be drawn, the Thesis presented a novel method, best to the authors knowledge, about using different timings features in embedded systems. The work is done on the implementation of AUTOSAR that represents the standard in software of modern vehicles. Since modern vehicles are under the threat from an attack and malicious third parties, *AutoSec* is used to detect anomalies in work of ECUs as a manifest of potential attack on the system in the vehicle. The results obtained by evaluating the algorithm showed significant improvements in direction of highly strict requirements and standards in automotive industry. The Research and Developed prototype throughout working on the Thesis, showed step up towards increased security measures for safer transportation. The new field detected by the Thesis shall be further researched and the contribution of the Thesis should be further deepened. Method and elements introduced by the Thesis could potentially find a way soon to the production line and become parts of the software in modern ECU protecting highly security risk elements in the car and thus providing safer environment.

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Declration

I hereby declare that the work presented in this thesis is entirely my own and that I did not use any other sources and references than the listed ones. I have marked all direct or indirect statements from other sources con- tained therein as quotations. Neither this work nor significant parts of it were part of another examination procedure. I have not published this work in whole or in part before. The electronic copy is consistent with all submitted copies.