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PERFORMANCE-BASED METHODS AND TOOLS FOR COMPETITIVE SAFETY IN AGRICULTURE

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Tesi di dottorato di:
Dott. Ing. Pierluigi Rossi
PhD student' s name and surname
Firma (Signature)

Coordinatore del corso
Prof. Ing. Andrea Luigi Facci
PhD Coordinator's name and surname
Firma Signature)

Tutore
Prof. Massimo Cecchini
Thesis Supervisor's name and surname
Firma (Signature)

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Performance-based methods and tools for competitive safety in agriculture

Pierluigi Rossi

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Contents

Abstract

Safety is a key aspect in agriculture and the sector is one of the most dangerous among working activities. Machinery, environmental conditions and poor training are just some of the main aspects which negatively influence accident rates. It must be noted although that most of the time there is not a main cause of failure, it rather is a mix of reasons which might be harmless if taken singularly but that may lead to severe accidents if combined.

The complexity of the working context is not given by complex machinery or tasks, but it is strongly affected by the presence of harsh working conditions, lack of proper training and hazards that cannot be eliminated. To deal with this context, a dynamic approach to safety is required: a popular and relatively new analysis method called Functional Resonance Analysis Method (FRAM) offers a good way for handling dynamic scenarios and the efficiency-thoroughness trade off (ETTO) which is constantly present in a working environment. FRAM also aims to describe every scenario (including accident scenarios) as generated by output variability among the tasks that an activity is made of, so that there are no more cause-effect analysis only but instead internal and external variability (this is why it is described as "functional resonance" analysis method). This work aims to exploit FRAM's concepts to create a safety analysis method which is specific for agricultural contexts and that allows to identify performance-based safety solutions that prevent production losses and ensure safe operations. The AECAT cycle of analysis (accident analysis, effectiveness working mode, compliance ode, as-low-as-reasonably-possible mode and thoroughness working mode) has been created to manage the evolution of agricultural activities as external variables influence them (weather, soil conditions, market demands, time, etc).

Practical applications of this method include safety management tools and artificial intelligence (AI) algorithms which can enhance safety and reliability for specific machinery. Both those applications have been analysed and tested in this thesis and further research can be made to extend the range of possible solutions.

1 Introducing a "Competitive Safety" strategy to unlock hidden production potential

The aim of the thesis is to elaborate a performance-based safety analysis method for agriculture and make it feasible for both standalone applications on machinery and safety management systems. Efforts have been made to identify agricultural accident trends in Europe and, from data analysis, enhance an existing qualitative analysis method in order to make it work as a semi-quantitative safety analysis method in agriculture. The main aspects covered by this research covered the following aspects:

- The integration of safety and production in agriculture through new technologies;
- Comparison of quantitative safety analysis and dynamic approaches to safety;
- The development of a performance-based Safety management method for Agriculture;
- Highlight how the Functional Resonance Analysis Method (FRAM) has been employed to develop a specific method for agricultural activities;
- The role of Artificial Intelligence (AI) and Machine Learning (ML) applied to dynamic safety assessments.

These five aspects will be better described in the following paragraphs, and will be utterly covered in specific chapters.

1.1 Integrating safety and production in agriculture through new technologies

Agriculture and forestry are dangerous working sectors and they struggle every year with a high number of fatal accidents and long-term injuries. Victims sometimes even include bystanders, children and any other nearby persons, apart from workers. Conditions, working environment, hazardous machinery and solitary activities make safety management a complex task even for smallholding farmers. With the coming of smart devices and a large use of electronics in agricultural vehicles and equipment, agriculture became more

technological but hazards did not melt away at all. Mechanisation remains vital for farmers but poor interaction with somewhat harder-to-understand instruments and autonomous vehicles could eventually increase the chances of accidents with severe consequences.
In order to achieve better working conditions and to manage the typical risks of agriculture and forestry, safety must play a key role in design of future machinery. Its management needs to be embedded with quality at any stage and risk should be analysed from everyday performances rather than merely from accident statistics. Recent advances in Internet of Things (IoT) devices can greatly be beneficial to agricultural safety, since data and low-cost sensors can be integrated in agricultural machinery for cheap prices. At the same time, digital farming can be considered expensive by many, but would carry anyway additional benefits regarding safety. Given such scenarios, methods and models that are meant to manage risk in agriculture and forestry are needed and must exploit the possibility of doing so in a dynamic way, rather than statically or just simply by following cause-effect safety analysis methods.

1.2 Safety analysis in agriculture: quantitative safety analysis and human error rate predictions vs. dynamic approaches

Reliability analysis has developed many methods for risk prediction and failure rate estimations during the last 50 years. The need for such methods was required by safer designs for industrial plants that could have been prone to major accidents hazards and by applications in which safety played a mission-critical role (energy production, transportation, etc). The usual outcome of probabilistic reliability assessments (PRA) consists in a failure rate, or a combination of failure rates (fault tree analysis and event tree analysis) or a human error probability (HEPs): this kind of output requires basic events to be described as "working" or "failed", so it only accepts boolean inputs such zeros and ones, there is no space for fuzzy logic or other ways to describe the state of a component. These boolean events add up in a cause-effect way and can produce the probability for a certain accident (called top-event, because it is at the apex of a pyramid made of basic events that are combined together) and damage estimations.

This shows why Boolean algebra isn't always feasible in safety analysis of complex systems: since there are many different failure modes which also involve partial failures or latent failures, it can result in an model that doesn't properly describe reality as it is. Rather than just describing the component as "working" or "not working", a non-binary model should be implemented instead to keep anomalies into account and let predictive maintenance increase the system's reliability. It should be also kept in mind that non-technological variables and human performance can hardly be described as technological components that just work or fail, hence a more fitting model is required.

Many reliability analysis tools and methods such as Fault Tree Analysis (FTA), Event Tree Analysis (ETA), What-If, Failure Mode and Effect Analysis (FMEA), describe accidents that happen in a precise sequence or when certain system functions completely fail. Despite such methods can be of great help to define accident probabilities and provide quantitative safety analysis, they can hardly keep track of those common causes of failure (CCF) which might led many system components to fail all at once: some methods, like FTA and ETA (which together form the "bow-tie" model) also cannot describe components' failure modes and describe the system as a chain of boolean gates (AND, OR, XOR, etc). Such limits also affect any final probabilistic safety assessment (PSA) on the long run: such biases in calculating top event probabilities can, in fact, result in frequencies of occurrence that highly exceed those estimations.

For many reliability analysis tools and methods systems fail only following a cause-effect chain of component failures. Non-major anomalies which can add up and result in major accidents sometimes cannot even be taken into account since the status of a component can only be described in boolean terms. Ad described in Charles Perrow's book "Normal Accidents", accidents can be also provoked by a series of unfortunate issues which lead to major consequences even if they are, taken individually, absolutely not catastrophic events and rather just day-to-day contingencies. The book also shows how, describing investigations that followed the Three Mile Island nuclear power plant accident in 1979, how different analyses carried by companies and institutions led to completely different outcomes, almost all of them involving one specific cause that should be held responsible for the accident: from the example taken from real life, it was clear that every analyst missed the bigger picture of a complex system that can have a large variety of unexpected behaviours and an even greater number of unexpected outcomes.

Human behaviour is a key aspect in probabilistic safety analysis, in what literature used to define as human error and human error probability (HEP). Many analysis models such the Technique for Human Error Rate Prediction (THERP) and Cognitive Reliability and Error Analysis Method (CREAM) focused on identifying which tasks in a particular activity can be affected by human actions or behaviours. These approaches, although very useful for systems' probabilistic assessments, did not really take into account how human behaviour can also positively affect a system's outcome and fix any small anomaly before it could lead to failure: increasing a task's complexity results in greater numbers of unexpected outcomes and weighty decisions that, more often, must be taken in a short time. From this point of view entire accident analyses could be revised: if a complex system has a large number of unexpected behaviours which are unpredictable even at system design stage, then every human operator is responsible for its outcomes and should take merits for every small adjustments done in order to fulfil system's tasks.

From binary systems such FTA and ETA that are based on boolean logic, and above all from systems based on thresholds like many compliance regulations, new methodologies based on fuzzy logic must be implemented in order to cover every possible state in which a system's component can be found.

An important feature of many hazard and risk analysis methods is the capacity to look forward and detect accident scenarios that have never happened before but that are a real possibility. It is the case of Hazard and Operability Analysis (HazOp), but despite being one of the few methods doing so, scenarios only arise node by node and effects on other system's nodes are investigated step by step. Gathering information on latent failures, possible single-failure accident conditions and all those conditions which might lead to an accident scenarios is vital for safety system but such information often becomes clear only after they arise: the key aspect of safety analysis shouldn't be providing prevention and protection measures after an accident, it should instead foresee accident conditions and to do so analysts should look at those dangerous conditions which are present while a system actually works, instead of just looking at what went wrong and find counter-measures. This approach aims to search for latent accident causes or conditions that can generate danger even if, at first glance, tasks are getting done without issues.

Such methods, as mentioned, are all based on models which fail to properly describe those components and functions that cannot be assessed by boolean algebra. In addition, human error probabilities also fail to show when system's accidents are prevented by human intervention. To summarise, here is a list of the limits of those systems when applied to agriculture:

- Work as imagined by system designers strongly differs from work as done by operators;
- Elements involved in activities cannot be easily described as working or not working. There are anomalies and working modes that need to be taken into account as well;
- Workers can adjust their performance according to how an activity is carried out, meaning that they can also end up having little or no time for particular safety procedures or simply cannot put them into place;
- Cause-effect relationships are responsible only of a small part of common accidents. Many of them are, instead, related to more than simply one cause and result from several hazardous behaviours or working conditions that happen altogether and that might not be responsible of any accidents if they are present alone.

On the other hand, newer analysis method can offer a dynamic approach instead, overcoming the oversimplification operated by probabilistic risk assessment methods. The Functional Resonance Analysis Method (FRAM), for instance, allows a much more flexible analysis and a qualitative output for safety assessment. The aim of this work is provide a semi-quantitative approach instead, by upgrading the existing functional resonance analysis methodology and designing it for the needs of safety assessments in agricultural contexts.

1.3 A Performance-based Safety management method for Agriculture

Safety and Production has often been seen as dichotomous aspects of farming production since emphasis on the first can result in a decrease for the latter. This concept, on the other hand, is further strengthened by necessities on the field: good timing for harvesting, climate change and contingencies can endanger production and completely deny any profit, leading to sacrificing any other good practice and compliance that contributed to the business' growth. Despite a resilient and lean safety management can reduce the impact of adverse events, it is the first to be sacrificed to - temporary - reduce the expenses and gain faster production.

The first step to achieve better safety workplaces in agriculture must then require a new framework that allows safety to be embedded into production, a flexible instrument which creates the opportunity to adapt risk management to production management and understand the best strategies and solutions for every workplace and season. Performance-based safety management approaches are already known in fire protection engineering, because every measure is not defined by thresholds and requirements given by national regulations: they can adapt every solution based on what requires fire protection and by its value, therefore any solution is specific for a certain workplace.

Once achieved performance-based dynamic safety assessments it will also be possible to integrate new technology in order to obtain information from a distributed net of sensors on machinery and in the environment. This would allow workers to realise when hidden dangers arise and might help production by adopting the most effective solutions without renouncing to safety. Artificial intelligence (AI), for instance, can be of great help in classifying hazardous situations and latent internal or external performance variability, just as predictive maintenance does. Classification of thoroughness operations, compliance to regulations or need to achieve higher efficiency can be easily detected in single functions as in more complex activities if proper task analysis has been performed "a priori". Recent developments in AI increased its capabilities in detecting human behaviours as well, which makes it even more interesting for safety applications: nowadays, even top automotive manufacturers as Tesla Motors do not relay on radars and LIDARs anymore, but focuses on smart AI technologies that are able to detect obstacles with greater reliability.

An entire chapter will be dedicated to AI solutions applied to agricultural machinery for safety purposes.

1.4 A dynamic approach to safety: Functional Resonance Analysis Method (FRAM)

The Functional Resonance Analysis Method (FRAM) aims to describe an activity by its basic functions, which are linked by variables such as inputs, outputs, preconditions, resources, timing and control. Those parameters describe a function but not all of them must be specified for each one: preconditions, control and resources, for instance, might not be required for the execution of a specific task. The set of functions that are required to carry out an activity are called FRAM instantiations: since functions can be linked in many ways to each other to perform the activity, it would not be possible to describe all the possibilites in one figure because it rather shows the way it has been carried out in that moment. Functions utterly divide into background and foreground functions, while their flow in a FRAM instantiation defines them as upstream and downstream functions.
Each function has up to 6 parameters: inputs, outputs, preconditions, controls, timing and resources. These can be visualised as an hexagon as follows and parameters of a function will be linked to another function if a given output from a function takes part in another one.

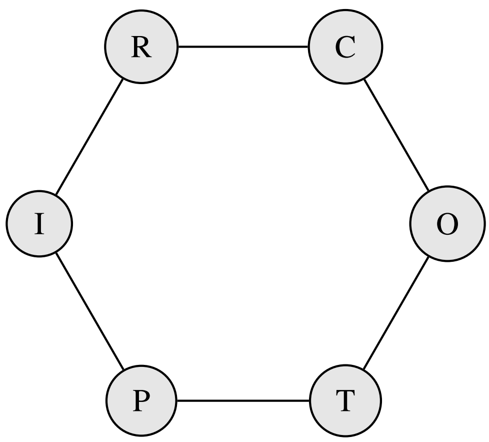


Figure 1: FRAM's graphical representation of a function

Those functions can be identified by Hierarchical Task Analysis (HTA) and links among functions may vary accordingly to how the activity is carried out every time.

Another important concept involved in FRAM functions is the ETTO principle. The whole FRAM is based, in fact, on the so called Efficiency-Thoroughness Trade-Off (ETTO principle) which refers to the inevitable trade-off between performing a certain task with precision and performing it as fast as possible to achieve the highest efficiency. If a task is carried out precisely, it will might result slow and not efficient: on the other hand, if the task is carried out fast, it might not be enough precise. The everyday activity for is affected by this trade-off and every small adjustment is based on the availability of time, resources and in the necessity (or possibility) to keep enough control on the outcomes or not.
The functional resonance analysis method will be further exploited to determine the most important instantiations, which are at least the following: accident scenarios, effectiveness working mode, compliance working mode, ALARP working mode and thoroughness working mode. Additional instantiations can be added in order to describe the ways in which an activity can be carried out in a dynamic way.

1.5 Artificial Intelligence (AI) and Machine Learning (ML) applied to safety assessment methods

A dynamic tool for safety management inevitably requires a large and reliable source of data, that can be provided by onboard sensors and environmental information from satellites, soil condition sensing and weather forecasts. Such data will also need to be handled and translated into valuable inputs for an algorithm that will assess the activities and establish what is needed to put into place to achieve a safe working environment.
Any kind of computer algorithm can be created to elaborate data and provide safety information: all those methods that include computer processing are called artificial intelligence. Most of the time it happens by hard-coding the ways that algorithms will have to produce alerts, signals, etc. This happens by setting thresholds, or by creating if-else statements for variables. Sometimes, although, the data flow is just too big and complex to be handled this way and tools which are more elastic are needed: machine learning and deep learning are, for instance, two important tools that can be exploited to create flexible algorithm that can adapt to any situation arising in working environments.
Machine learning algorithms can be implemented to detect internal variability in a FRAM

function simply by detecting any variation in its components given a training dataset which helps to define what can increase it, what keeps it stable and what dampens it. On the other hand, further classification is needed to understand when a background function affects the system's variability, and link it to classify the task as performed at low or high resonance. It could also be used to better define qualitative risk analysis (low, medium and high risk) or to provide real-time information to workers as they perform their activities.
One of the most popular machine learning's algorithms is the Random Forest (RF), which is based on the generation of a fair quantity of decision trees made by picking a certain number of features (variables) inside a dataset and try to guess their relative label: the algorithm will try to predict the label by checking which one was the most predicted among the decision trees. The advantage is that RF can be trained with relatively small amount of data, for instance, even hundreds of rows are enough; on the other hand, although, every row in the dataset must be labelled and this is why such algorithms are called supervised since they must train on datasets which already contain the right answers (labels).
RF can do both classification and regression, so it can establish which label is the most appropriate for a row of data. It must be said that it cannot perform predictions outside its training dataset's domain: for example, if it gets trained on data like hourly wages (i.e. 20 € for 1 hour, 60 € for 3 hours, etc) it can predict wages inside its domain (for instance, it will predict 40 € for 2 working ours) but it won't be able to do so outside of its domain (it will predict the highest value, i.e. 60 €, even for an 8 hours shift).
Algorithms like random forests can be implemented to identify the proper FRAM instantiation in which a system falls for every moment of an activity. This can be done live, so that the algorithm might provide alerts to the workers through the machinery they use or on mobile phones. This will be further investigated in a specific chapter.

2 Accident trends in agriculture from the EUROSTAT database

2.1 Statistics: understanding how and why fatalities and severe injuries happen

Occupational health and safety is a subject that can be studied from a statistical point of view. Accident statistics, including both fatal and non-fatal severe accidents, are collected all over the world and can provide useful information for designing new legislative frameworks. Statistics, first of all, are biased by what does not get tracked: it might be due to simplified regulations that avoid accident communications to health and safety authorities if outcomes are not severe (i.e. less than 4 days prognosis) or it might be due to undeclared work or hobbyist activities. Even if it is possible to analyse only what gets communicated to the authorities, gathering such data can still represent the main instrument to understand the bigger picture of safety management at work in every country or region.

In Europe, the EUROSTAT [1] statistical office is responsible of tracking such data and produce quality statistics regarding every working sector: yearly information can be found by accident mode, by type of activity and also by type of consequence or involved body part. These data are reported as pure numbers in the Health and Safety at Work database (n2-07) and subdivided by activity (Agriculture, forestry and fishing) and type of injury.

Despite such a huge source of data regarding accidents, direct comparisons are not possible: countries have different legislative framework not only regarding safety management at work, but also on how they report their accident data to the EUROSTAT database itself. Differences among numbers should also be correlated to the working population in agricultural sector, and in this sector seasonal workers can produce big differences even among semesters of the same year in the same country.

Such data heterogeneity, although, shall not be seen as an ultimate obstacle for statistical analysis. Trends for each countries, for examples, can still be evaluated and compared; particular accident modes can also be analysed and generate questions for further investigations and future research.

2.2 The EUROSTAT database: agricultural accidents

Accident modes represent a valuable source of information to understand which are the most hazardous working activities and the most probable outcome. EUROSTAT database splits them in a large variety that can be summarised as follows:

- Wounds and superficial injuries (codes in the database: label 10, sub-labels 11, 12, 19);
- Bone fractures (code: 20);
- Dislocations, sprains and strains (code:30);
- Traumatic amputations (loss of body parts, code:40);
- Concussion and internal injuries (code:50);
- Burns, scalds and frostbites (code:60);
- Poisoning and infections (code:70);
- Drowning and asphyxiation (code:80);
- Effects of sound, vibrations and pressure (code:90);
- Effects of extreme temperatures, light and radiations (code:100);
- Shock (code:110);
- Multiple injuries (as the previously listed ones, code:120);
- Other specified injuries not included under other headings (code:999).

These labels can have additional sub-categories, which help to categorise them properly especially if their category refers to various types of injury, as many of the labels do.

A table containing EUROSTAT codes for injuries is reported as follows.

Code	Label
0	Type of injury unknown or unspecified
10	**Wounds and superficial injuries**
11	Superficial injuries
12	Open wounds
19	Other types of wounds and superficial injuries
20	**Bone fractures**
21	Closed fractures
22	Open fractures
29	Other types of bone fractures
30	**Dislocations, sprains and strains**
31	Dislocations and subluxations
32	Sprains and strains
39	Other types of dislocations, sprains and strains
40	**Traumatic amputations (Loss of body parts)**
50	**Concussion and internal injuries**
51	Concussion and intracranial injuries
52	Internal injuries
59	Other types of concussion and internal injuries
60	**Burns, scalds and frostbites**
61	Burns and scalds (thermal)
62	Chemical burns (corrosions)
63	Frostbites
69	Other types of burns, scalds and frostbites
70	**Poisonings and infections**
71	Acute poisonings
72	Acute infections
79	Other types of poisonings and infections
80	**Drowning and asphyxiation**
81	Asphyxiation
82	Drowning and non-fatal submersions

Code	Label
89	Other types of drowning and asphyxiation
90	**Effects of sound, vibration and pressure**
91	Acute hearing losses
92	Effects of pressure (barotrauma)
99	Other effects of sound, vibration and pressure
100	**Effects of temperature extremes, light and radiation**
101	Heat and sunstroke
102	Effects of radiation (non-thermal)
103	Effects of reduced temperature
109	Other effects of temperature extremes, light and radiation
110	**Shock**
111	Shocks after aggression and threats
112	Traumatic shocks
119	Other types of shocks
120	**Multiple injuries**
999	**Other specified injuries not included under other headings**

Table 1: Code definitions in EUROSTAT database

Such labels can involve different types of equipment: for instance, tractors or operating machines can represent a higher number of accidents involving loss of body parts compared to load handling. A table summarises which hazards refer the most to particular elements such as loads, barriers, machines and tractors.

Label	Barriers	Loads	Machines	Tractors
Wounds and superficial injuries	Yes	Yes	Yes	No
Bone fractures	Yes	Yes	Yes	Yes
Dislocations, sprains and strains	Yes	Yes	No	No
Traumatic amputations (Loss of body parts)	No	No	Yes	Yes
Concussion and internal injuries	Yes	No	Yes	Yes
Burns, scalds and frostbites	No	No	No	Yes
Poisonings and infections	No	No	Yes	No
Drowning and asphyxiation	No	No	No	Yes
Effects of sound, vibration and pressure	Yes	No	Yes	No
Effects of temperature extremes, light and radiation	Yes	No	No	No
Shock	No	No	Yes	Yes
Multiple injuries	Yes	Yes	Yes	No

Table 2: EUROSTAT accident causes and their possible sources

From the previous table it is possible to identify which accident modes are typical of machinery or of manual work. On the other hand, it is not really possible to identify specific accident modes which are exclusively related to only one source of hazard. Given the type of data that is possible to handle in the Health and Safety at Work database from EUROSTAT, trends can be analysed for every country of the European Union.

2.3 Severe accidents and fatal accident statistics by EU country

EUROSTAT database on Health and Safety at Work allows to retrieve data since 2007. In order to provide a reliable source of data for statistical analyses, a period starting from 2009 to 2018 has been identified, generating plots through R statistical software. Accidents are split in two categories:

- Accidents which required at least 4 days to recover;
- Fatal accidents.

Country/Year	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
EU - 27 countries (from 2020)	:	158.295	159.224	144.379	151.968	170.180	163.354	162.238	148.734	:
EU - 28 countries (2013-2020)	:	164.079	165.444	151.445	158.369	178.004	170.687	169.275	155.791	:
EY - 27 countries (2007-2013)	169.353	163.484	164.731	150.817	157.812	177.495	170.053	168.641	155.121	:
EU - 15 countries (1995-2004)	160.560	159.015	158.215	144.439	151.599	171.153	163.746	162.300	149.001	:
Belgium	406	384	468	370	352	359	339	408	386	399
Bulgaria	49	64	55	65	59	67	72	40	66	53
Czechia	4.842	340	2.712	2.578	2.668	2.628	2.533	2.530	2.482	2.491
Denmark	1.114	1.083	1.140	1.197	1.270	1.210	1.052	1.169	1.201	1.308
Germany	63.430	68.233	66.919	64.602	64.981	66.150	62.165	64.543	53.209	47.728
Estonia	297	306	316	273	381	377	305	287	246	312
Ireland	318	1.012	407	580	2.081	1.994	1.908	1.121	871	1.135
Greece	228	223	220	298	196	91	93	82	108	119
Spain	25.012	24.781	24.220	21.880	23.982	26.246	27.568	27.647	29.384	29.424
France	464	368	547	554	507	16.134	16.279	16.432	14.191	:
Croatia	:	596	713	629	557	509	634	634	670	711
Italy	45.513	43.237	40.003	36.092	33.797	32.631	31.190	29.298	27.723	26.780
Cyprus	59	48	38	36	28	31	26	42	34	61
Latvia	34	59	59	63	63	71	75	74	80	111
Lithuania	89	123	128	128	140	170	150	142	171	155

Country/Year	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Luxembourg	159	158	139	137	152	156	134	145	119	130
Hungary	852	815	658	891	697	757	762	998	713	620
Malta	49	29	31	27	25	22	22	23	17	27
Netherlands	2.425	270	1.171	1.127	3.172	2.369	544	344	1.450	2.026
Austria	6.823	6.644	5.556	4.659	4.515	4.738	4.009	4.071	4.232	4.479
Poland	1.273	1.436	1.433	1.395	1.208	1.217	1.272	1.207	1.300	1.120
Portugal	5.890	5.242	4.979	4.227	4.795	6.333	6.586	5.813	4.818	:
Romania	155	167	151	158	140	144	170	191	202	193
Slovenia	454	428	401	217	233	375	398	321	312	298
Slovakia	641	654	535	546	572	484	523	486	497	527
Finland	1.056	1.000	4.770	1.040	4.483	4.271	3.719	3.664	3.720	3.523
Sweden	533	595	601	608	565	646	585	523	533	595
United Kingdom	7.189	5.784	7.074	7.067	6.401	7.825	7.334	7.037	7.056	6.739
Great Britain	:	:	:	:	:	:	:	:	:	:
Iceland	:	:	:	71	:	:	:	:	:	:
Norway	786	519	348	617	265	167	216	221	214	228
Switzerland	1.528	1.547	1.555	1.630	1.696	1.614	1.747	1.719	1.623	1.748

Table 3: Yearly accidents by country

As already mentioned, not every country reports data in the same way: despite data is collected by following precise standards (codes), some data might be missing. That is why accidents are reported as occurrences: to overcome such issue, data has been normalised by dividing accident statistical data by the active working population in that country, in that sector and in that precise year; this way it has been possible to show data in graphs with accidents happened every year per 1000 workers. Number of workers per year in every country is part of another dataset, expressed by every trimester (EUROSTAT database LFSQ-EISN2, "Employment by occupation and economic activity from 2008 onwards, NACE Rev. 2").

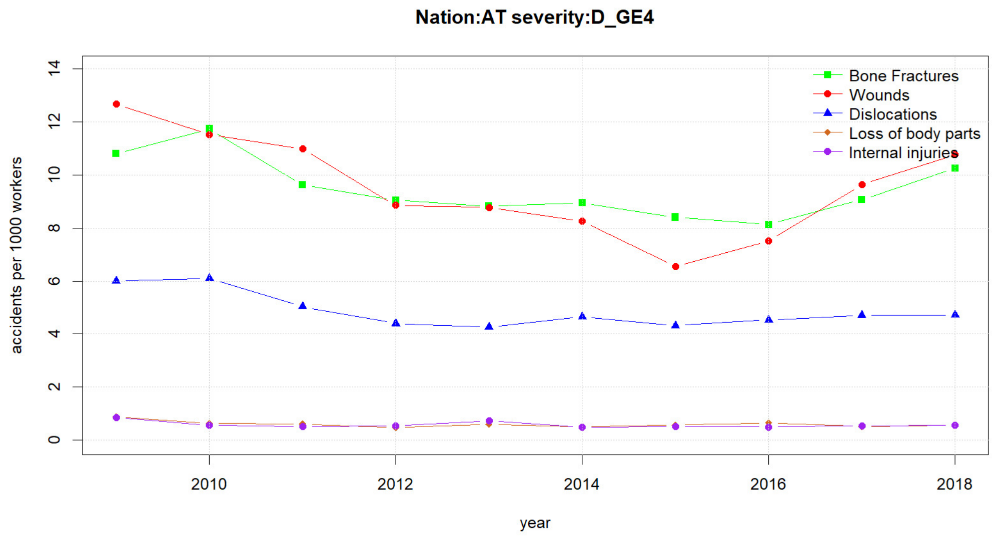


Figure 2: Agricultural severe accident cases trends: Austria

The above graph shows five of the most common accident modes present in the EUROSTAT database (green:bone fractures; red: wounds; blue: dislocations; orange: loss of body parts; violet: internal injuries). Is it clear that in the case of Austria, the most frequent severe accidents involve bone fractures and wounds: fractures are usually related to animal handling, use of tractor or other agricultural machines, while wounds might be related to a large variety of agricultural activities. The trend appears to be constant in recent years, despite a slight increase in 2017 and 2018.

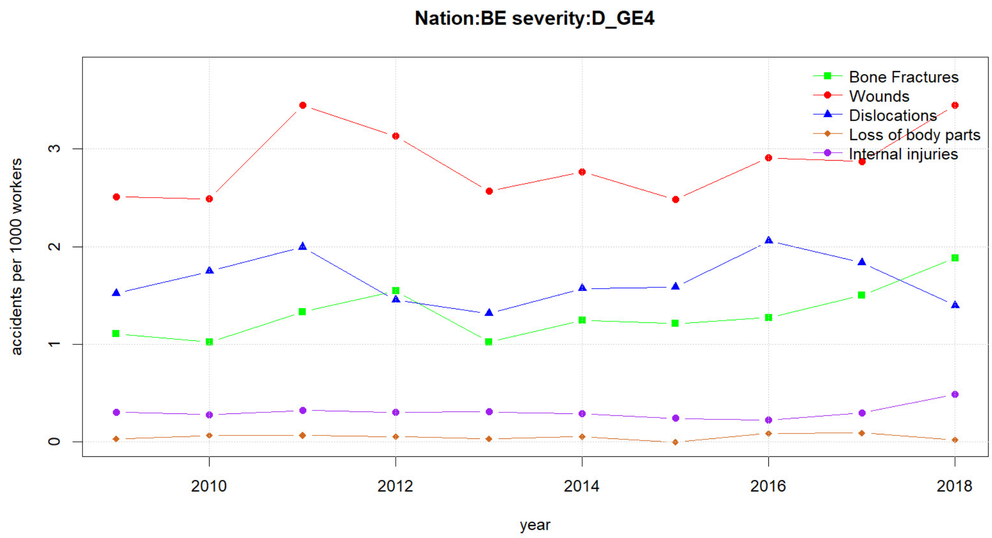


Figure 3: Agricultural severe accident cases trends: Belgium

In the case of Belgium instead, wounds is the most frequent severe accident mode and it might be related to a higher use of agricultural machinery. Even for Belgium, trends appear not to decrease with time.

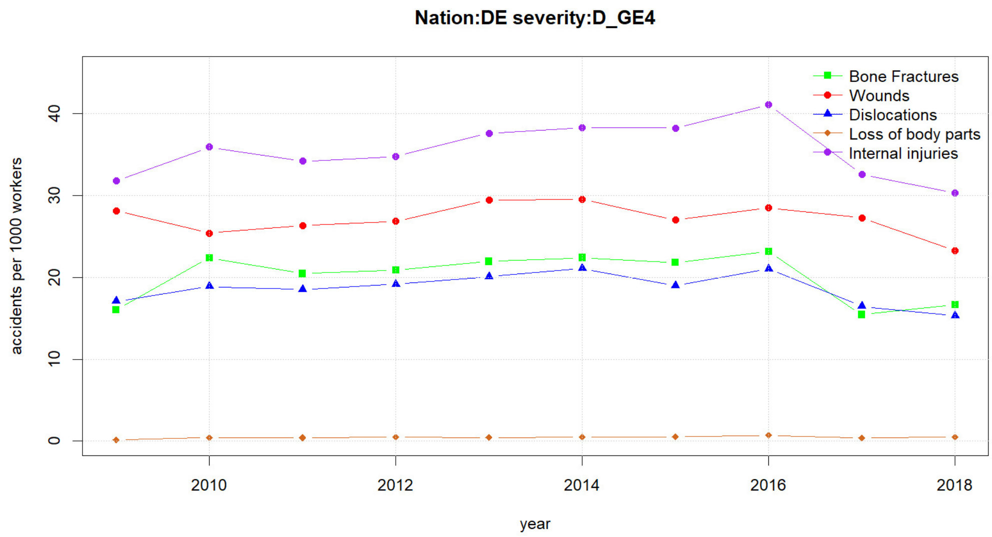


Figure 4: Agricultural severe accident cases trends: Germany

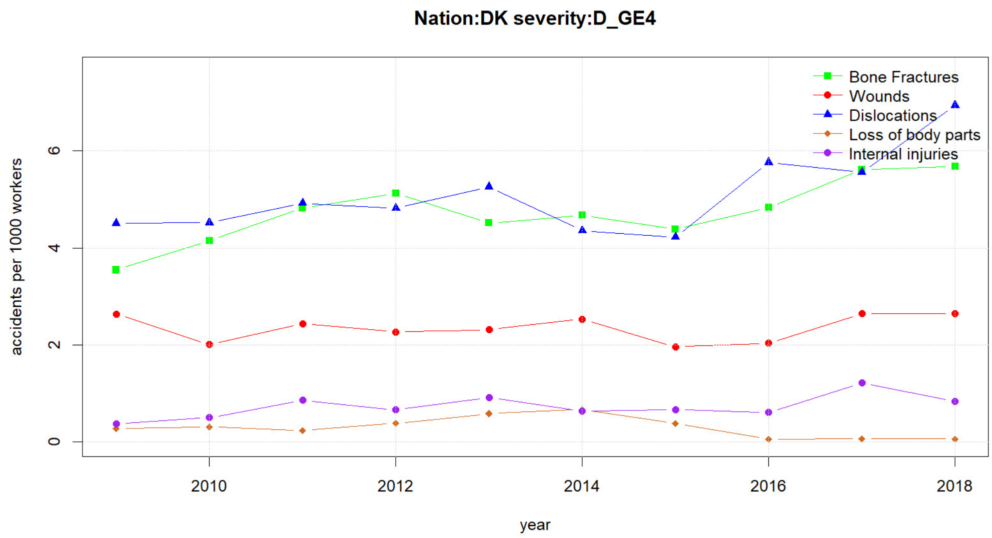


Figure 5: Agricultural severe accident cases trends: Denmark

Both Germany and Denmark report similar trends. Dislocations are the most frequent non-fatal agricultural accident in Denmark and, in that case, trend seems to be increasing with time.

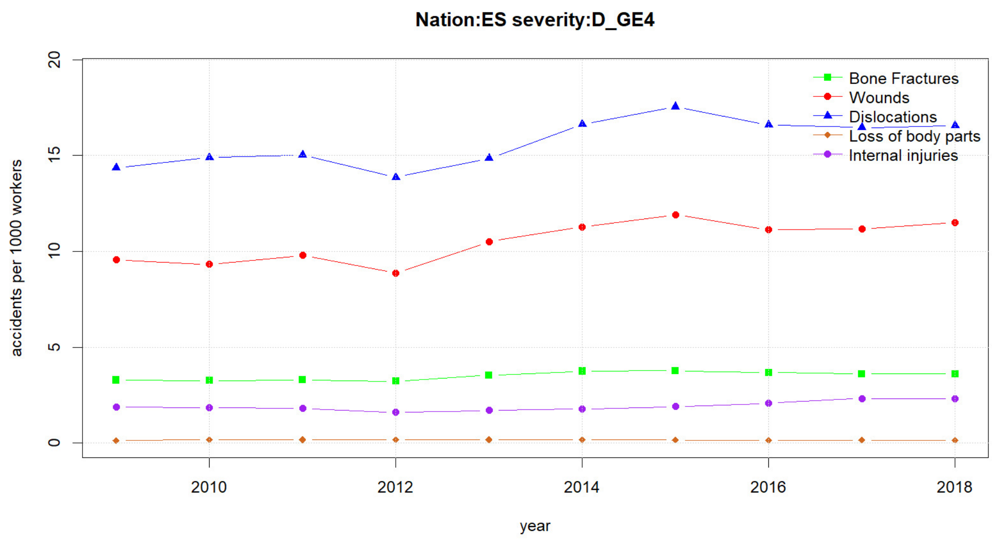


Figure 6: Agricultural severe accident cases trends: Spain

Spain can be compared to Belgium, having dislocations and wounds as the most frequent accident modes. In that case, although, bone fractures are less relevant in the database and might be due to a higher use of manual work (fruit picking, vineyard activities, etc). Trends, in that case as well, increase with time.

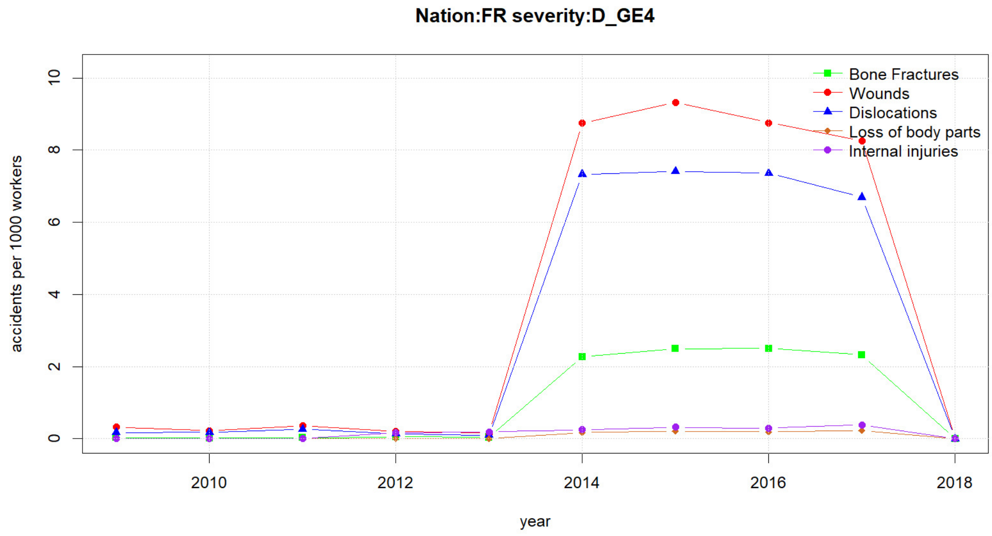


Figure 7: Agricultural severe accident cases trends: France

Data regarding France report an odd trend, with low values in years 2009-2013 and a high rise in the recent years: it might be due to changes in regulations which involved a higher number of accident at work notifications as a result.

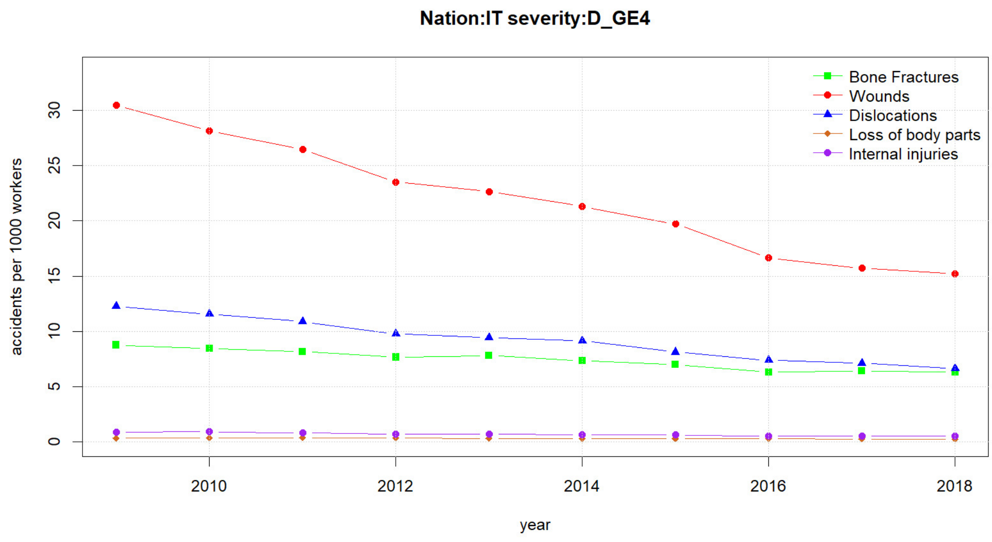


Figure 8: Agricultural severe accident cases trends: Italy

Italy displays a rare case of decrease in the occurrence of accidents at work in agriculture. Despite that negative trend, rates appear to be constant.

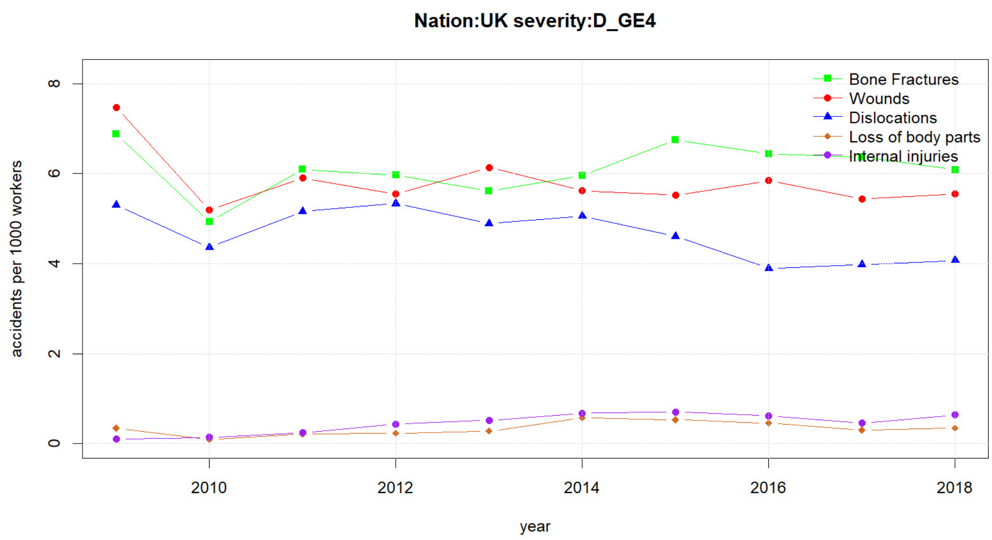


Figure 9: Agricultural severe accident cases trends: United Kingdom

United Kingdom data shows an equal impact of bone fractures, wounds and dislocations among the most common accident causes in agriculture. Trends are constant in that case. Now it is worth looking at fatal accidents instead, for each one of the previous countries.

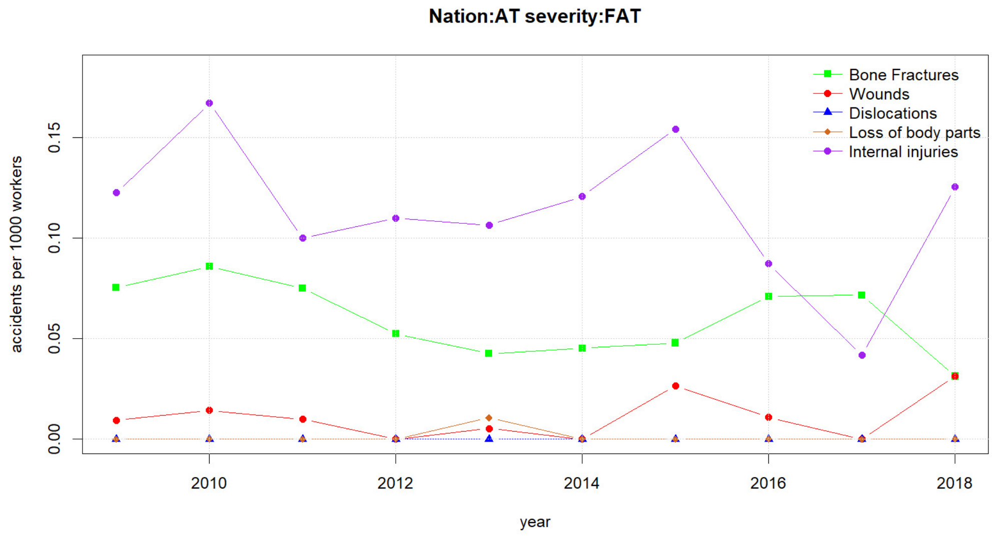


Figure 10: Agricultural fatal accidents trend: Austria

Internal injuries are the most frequent accident mode for fatal accidents in agriculture. That is not only related to Austria, it is a rather common issue instead: it is highly affected by tractor rollovers, which are the cause of most of fatal accidents in agriculture.

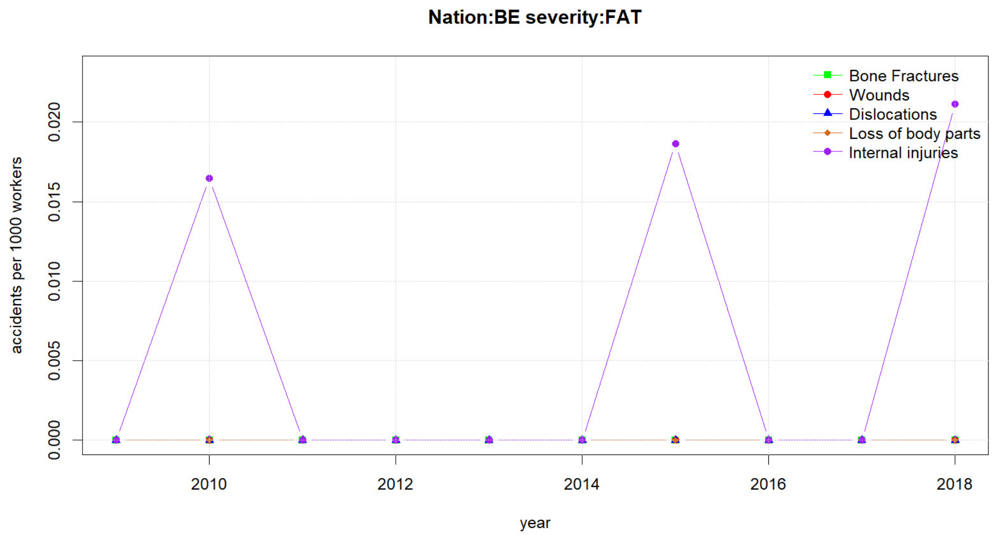


Figure 11: Agricultural fatal accidents trend: Belgium

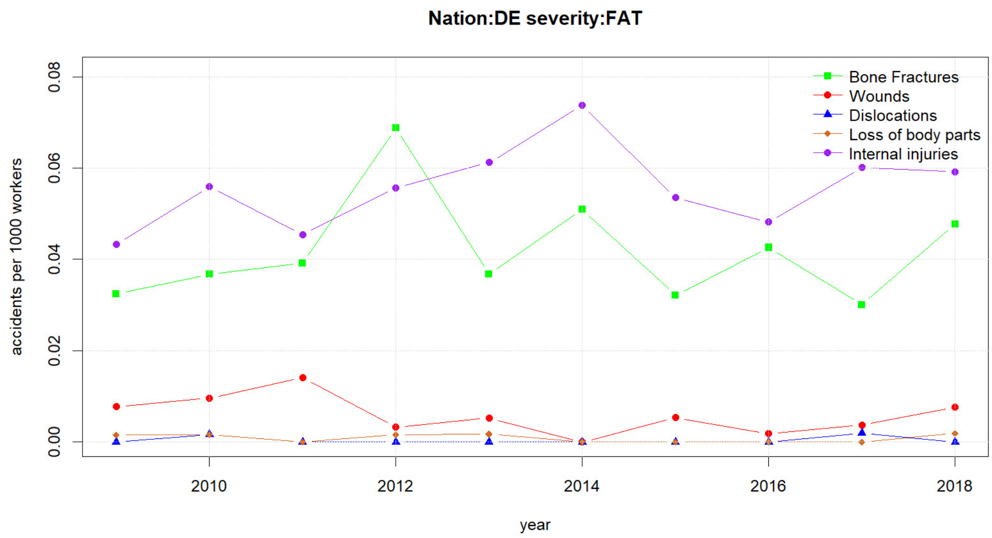


Figure 12: Agricultural fatal accidents trend: Germany

Bone fractures represent another major cause of fatal accidents in agriculture. It can be related to agricultural machinery and to accidents related to tractors. Trends appear to be quite constant as seen for non-fatal accidents.

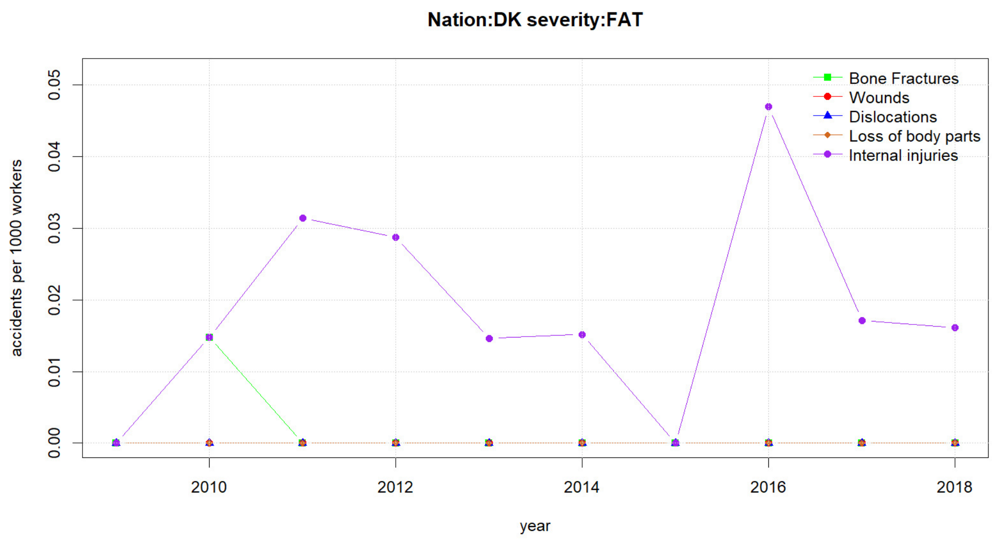


Figure 13: Agricultural fatal accidents trend: Denmark

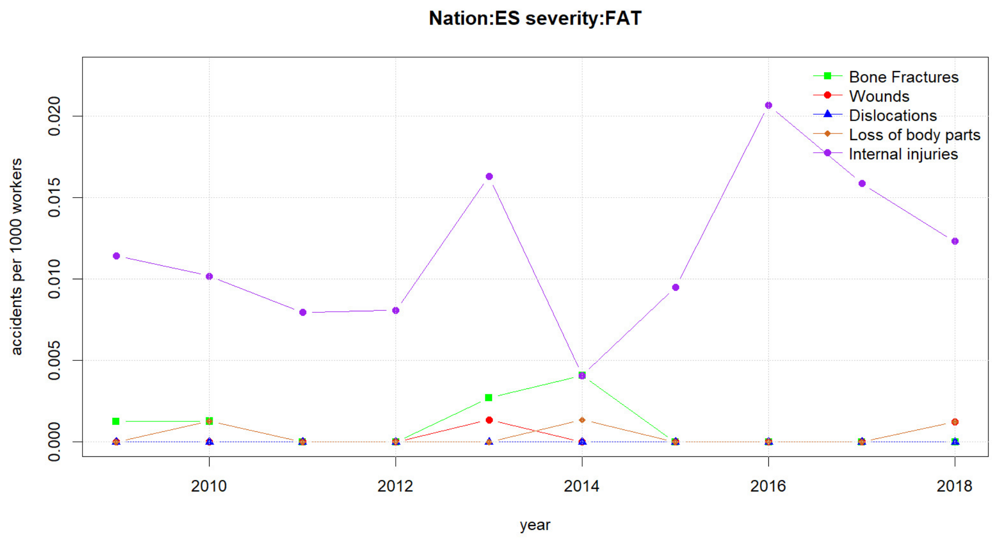


Figure 14: Agricultural fatal accidents trend: Spain

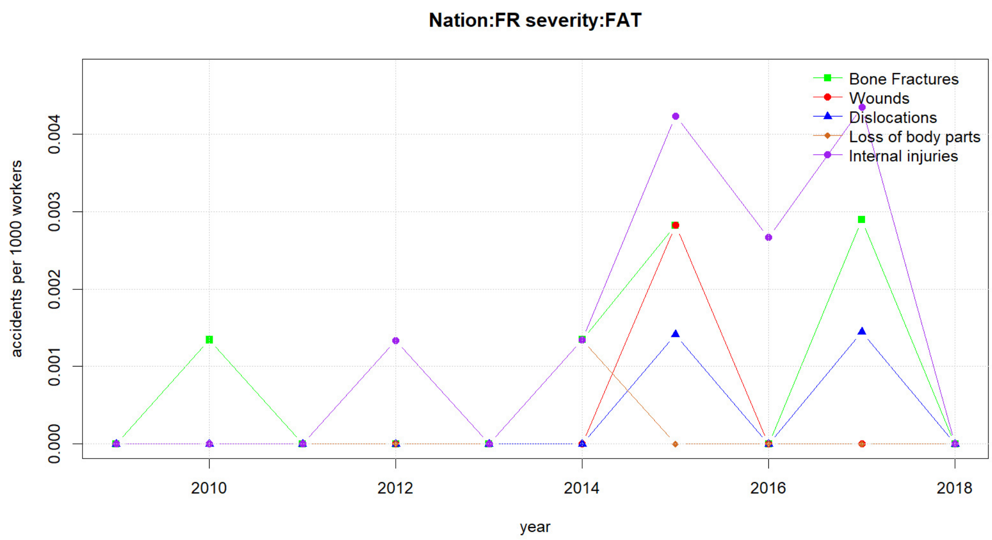


Figure 15: Agricultural fatal accidents trend: France

France confirms to be an unique case regarding fatal accidents in agriculture as well. Database shows accidents involving not only bone fractures and internal injuries but also dislocations, loss of body parts and wounds. It can be due to many different types of farming businesses which can involve a large use of machinery in different contexts.

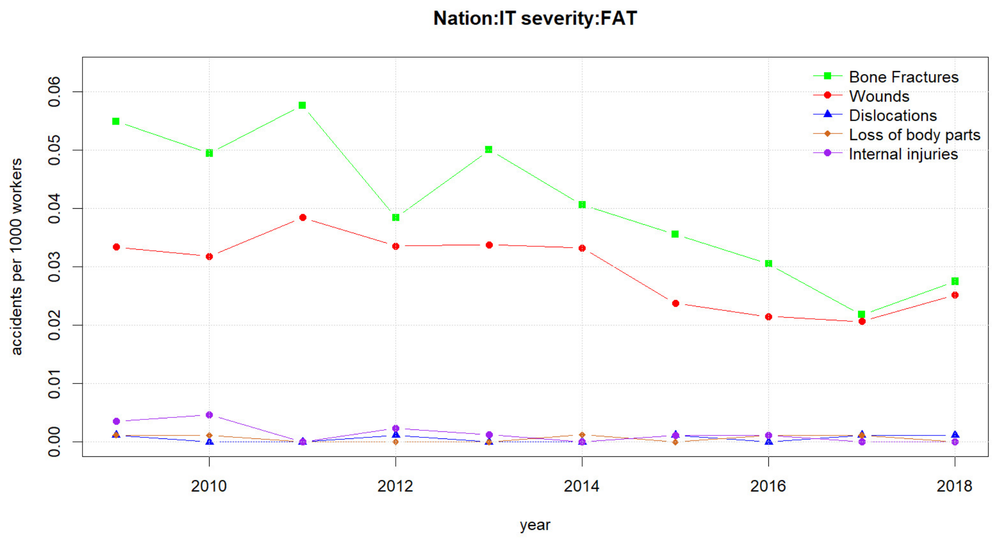


Figure 16: Agricultural fatal accidents trend: Italy

Even on fatal accidents Italy appears to be the only one country with a - slightly - negative trend in the last years. Bone fractures and wounds are the most common causes, for the reasons that have already pointed out regarding the use of machinery and tractors.

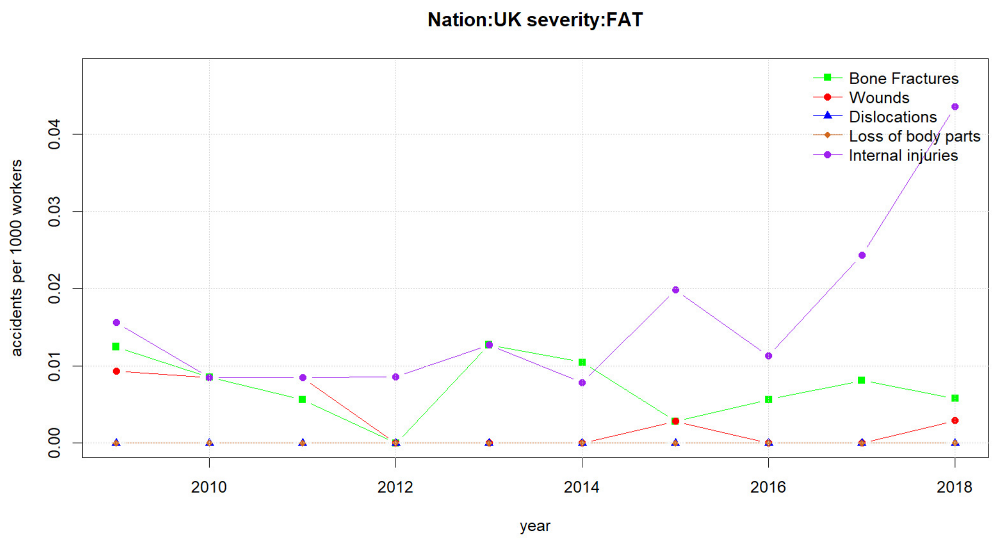


Figure 17: Agricultural fatal accidents trend: United Kingdom

EUROSTAT database shows a constant trend for United Kingdom's fatal accidents as well, with an increase of fatal accidents due to internal injuries in 2017 and 2018.

2.4 Health and safety at work: the contact mode of an injury

The EUROSTAT health and safety at work database does not only contain information regarding accident statistics. It also contains information regarding the contact mode of every accident, which is the HSW-PH3-08 EUROSTAT database. The database shows incidence rate for such accident mode in agriculture from 2014 to 2020, while contact modes are subdivided into 9 categories as follows:

- Contact with electrical voltage, temperature, hazardous substances - not specified
- Drowned, buried, enveloped - not specified
- Horizontal or vertical impact with or against a stationary object (the victim is in motion) - not specified
- Struck by object in motion, collision with - not specified
- Contact with sharp, pointed, rough, coarse Material Agent - not specified
- Trapped, crushed, etc. - not specified
- Physical or mental stress - not specified
- Bite, kick, etc. (animal or human) - not specified
- Other Contacts - modes of Injury not listed in this classification

The contact mode "Struck by object in motion, collision with - not specified" is of particular interest for safety in agriculture since its strongly related to the use of agricultural machinery, and will be deeply analysed in this work. First of all, it must be specified that incidence rates are available for this dataset: such incidence rates are calculated, according to the European Statistics on Accidents at Work (ESAW) database methods, as the ratio between the number of accidents (non-fatal or fatal for a given year, country, sector, sex, age group or other breakdowns) and the corresponding number of employed persons (reference population) multiplied by 100,000.

Country/Year	2014	2015	2016	2017	2018	2019	2020
EU27 (from 2020)	186.57	190.52	202.83	182.52	182.92	155.45	121.4
EU28 (2013-2020)	192.22	202.41	206.22	188.47	185.44	-	-
EU27 (2007-2013)	191.73	202.42	205.58	187.49	184.98	-	-
Belgium	278.35	74.69	223.25	274.47	222.14	200.63	226.58
Bulgaria	28.29	26.42	12.66	13.89	8.08	18.05	11.98
Czechia	0	0	0	0	0	0	0
Denmark	257.42	176.6	185.81	200.69	246.62	463.53	297.11
Germany	48.41	42.3	52	25.22	20.31	20.05	16.6
Estonia	99.68	147.76	242.96	113.72	158.48	294.34	346.54
Ireland	293.44	124.93	211.39	114.16	259.99	169.21	35.48
Greece	5.63	47.79	27.37	21.43	2.77	3.49	3.82
Spain	646.03	697.48	681.88	708.75	718.2	713.57	620.01
France	1400.89	1461.89	1540.11	1525.71	653.67	1584.44	16.32
Croatia	275.16	200.61	312.23	332.49	236.19	461.28	175.37
Italy	405.97	382.04	286.65	47.06	60.3	193.45	153.18
Cyprus	44.44	45.95	38.96	148.62	113.26	83.77	22.18
Latvia	80.84	45.6	79.75	67.94	125.55	50.46	105.56
Lithuania	21.43	11.3	19.51	32.1	14.32	31.03	28.11
Luxembourg	351.29	398.82	868.17	518.73	632	814.43	452.74
Hungary	82.32	71.86	85.08	61.04	47.85	56.91	61.04
Malta	246.86	199.49	231.79	229.68	213.84	155.23	247.02
Netherlands	0	0	0	0	226.57	0	0
Austria	399.14	360.72	738.36	790.18	432.47	395.86	366.78
Poland	15.58	14.87	15	45.98	47.41	16.18	38.35
Portugal	220.33	287.02	222.25	260.48	207.37	271.01	243.4
Romania	33.74	28.91	29.94	37.4	31.78	2.42	40.43
Slovenia	576.85	684.77	475.68	488.15	407.12	234.88	197.44
Slovakia	82.28	123.01	126.69	139.75	192.53	130.2	107.34
Finland	365.83	227.27	280.51	307.11	345.33	205.75	313.85
Sweden	76.96	75.73	58.35	53.62	83.51	83.74	0

Country/Year	2014	2015	2016	2017	2018	2019	2020
Iceland	-	-	-	-	-	-	50.9
Norway	54.5	103.21	124.56	111.15	92.97	60.47	93.1
Switzerland	625.14	556.03	857.4	654.4	830.2	1001.97	-
United Kingdom	353.85	407.76	283.03	310.04	238.15	-	-

Table 4: Yearly incidence rates by country

Data from previous table can be further analysed for every single country in the period 2014-2020 for non-fatal accidents only and, to be more specific, accidents that result in a period of absence from work greater than 3 days. That is, in fact, the type of distinction that EUROSTAT health and safety at work database does to distinguish non-fatal accidents from fatal accidents and also from accidents with limited consequences.
Despite the data is reported as incidence rate, there are great differences among countries. Some of them show really high rates of incidence, such as France and Switzerland; some others instead, like Germany and Poland, show extremely low rates. This is an issue related to the number of workers that has been taken as parameter in incidence rate formula and to the rules that regulate the required actions that companies need to carry out after an injury, which might result in simplified notifications for smallholders and therefore a reduction of incidence rates: despite the same criteria have been followed for the whole dataset, it must be highlighted that agricultural workers cover very different activities and accidents that involve collisions or being struck by machinery should only count those workers that were actually involved in activities that had been carried out with the help of machinery or tractors. This type of analysis, although, would be difficult to perform and other biases might still appear (categories would be needed to differentiate driver worker, on-foot worker, bystander, etc).

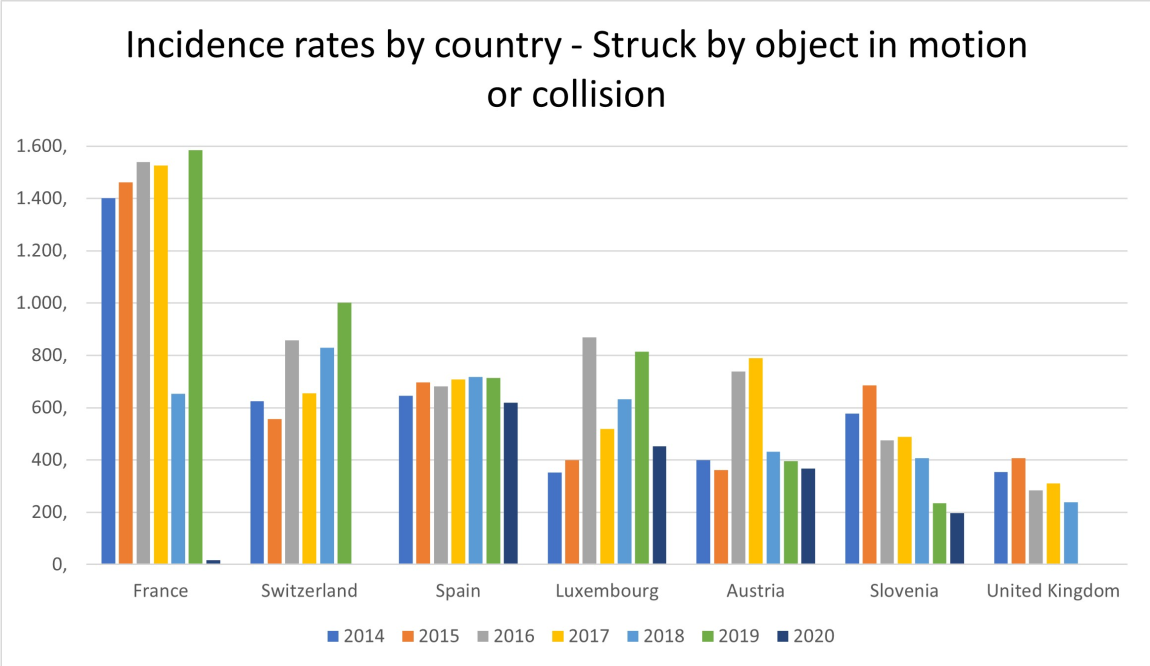


Figure 18: Incidence rates by country - Struck by object in motion or collision

France has the highest incidence rate regarding agricultural workers being struck by objects in motion or being involved in a collision, in the whole 2014-2020 period. Its trend also seems to be increasing with time, just as some other countries like Switzerland. Other countries like Slovenia and United Kingdom, despite reporting high incidence rates, show instead a downward trend; Spain seems to be an exception, since its trend is stable over time.

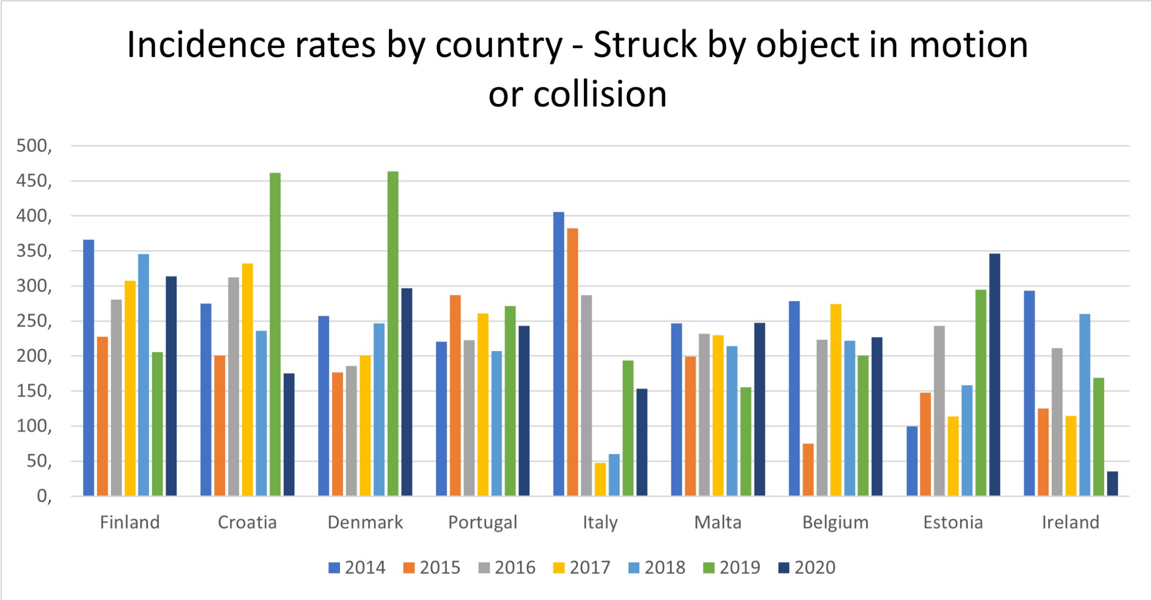


Figure 19: Incidence rates by country - Struck by object in motion or collision

Some other countries also report high incidence rates, sometimes even reaching a range of 300-500 accidents per 100,000 workers in the agricultural sector. Trends seem to be, again, increasing year after year with rare exceptions like Portugal, which trend is instead stable. Croatia and Denmark had peaks in 2019, and it seems to highlight a particular pattern if compared to the previous figure (France, Switzerland show an increase for 2019 as well).

Other countries show incidence rates below 200 cases per 100,000 agricultural workers. Given the different contexts that are typical of the countries that shown in next figure, it is hard to identify a specific pattern to explain data: it is also problematic to establish future trends since incidence rates are somehow very low compared to other countries.

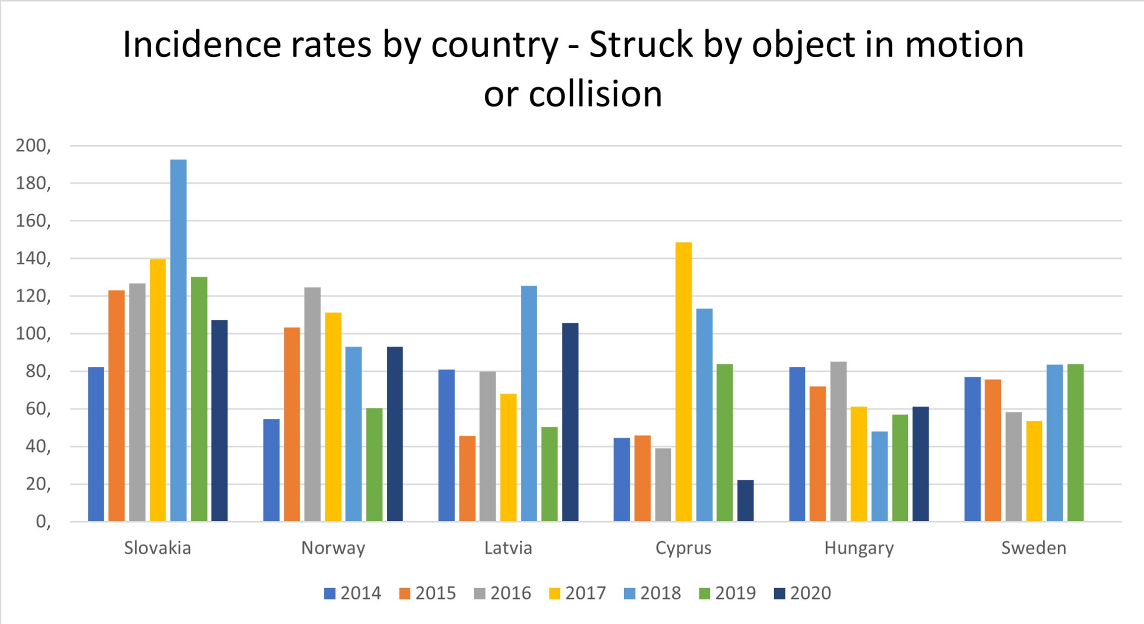


Figure 20: Incidence rates by country - Struck by object in motion or collision

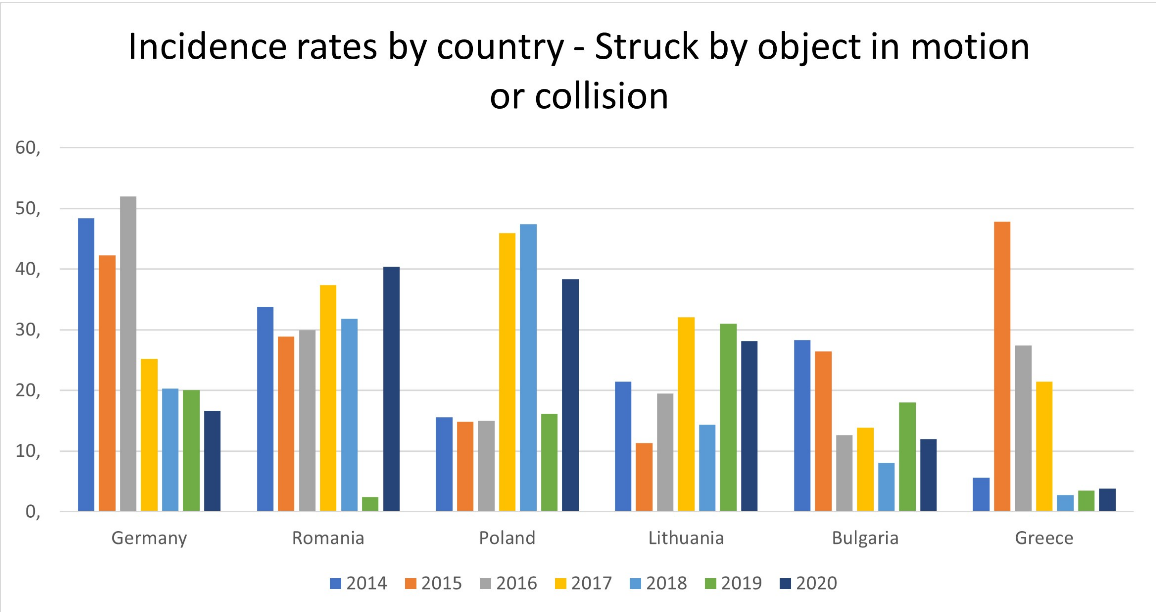


Figure 21: Incidence rates by country - Struck by object in motion or collision

There are particular cases in which the incidence rate is extremely low. This is the case of Germany, Romania and Poland. This might be due to a high number of workers employed in the sector compared to those that are effectively exposed to hazards involving machinery, tractors or any other kind of equipment in motion. It is worth, then, to look at specific trends in the number of non-fatal accidents (more than 3 days of absence from work) rather than incidence rates for those countries.

Country	2014	2015	2016	2017	2018	2019	2020
EU 27	16.921	16.712	16.269	12.889	13.410	14.884	8.824
Belgium	58	40	51	60	53	50	59
Bulgaria	23	22	11	12	10	14	9
Czechia	-	-	-	-	-	-	-
Denmark	173	121	141	188	173	180	201
Germany	1.592	1.393	1.695	738	591	581	492
Estonia	24	28	44	26	35	43	46
Ireland	320	130	224	126	279	174	36
Greece	27	22	30	23	13	14	14
Spain	4.098	4.397	4.394	4.677	4.799	5.317	4.448
France	4.410	4.548	4.708	4.069	4.346	4.455	49
Croatia	150	152	157	167	162	141	118
Italy	3.295	3.220	2.534	410	526	1.758	1.397
Cyprus	4	4	5	13	9	8	1
Latvia	18	16	17	17	28	23	23
Lithuania	11	6	10	16	7	14	10
Luxembourg	24	27	27	18	22	28	16
Hungary	110	105	126	98	70	83	94
Malta	6	6	6	5	5	4	7
Netherlands					186		
Austria	794	678	612	624	690	587	568
Poland	268	275	242	268	252	229	160
Portugal	857	983	708	793	610	732	628
Romania	39	35	38	49	42	43	53
Slovenia	96	113	76	77	65	71	58
Slovakia	68	73	73	75	84	70	57
Finland	379	239	285	285	276	183	279

Country	2014	2015	2016	2017	2018	2019	2020
Sweden	77	75	55	55	77	81	
Iceland							4
Norway	14	33	41	38	32	36	33
Switzerland	341	300	301	320	360	300	
United Kingdom	1.122	1.448	1.002	1.073	834		

Table 5: Yearly non-fatal accidents by country

It is clear from the previous table that some country just report few accidents at work in agriculture of that type. Even if some of them have fewer inhabitants and fewer farming businesses, they just report less accidents than expected (Greece, Estonia, Romania, Latvia). Spain and France have roughly the same number of non-fatal accidents at work in agriculture involving machinery in motion, but incidence rates are doubled for the latter. It is also worth considering that just these two countries represent half (or even more, in some years) of the overall number of accidents of that type in Europe.

2.5 Outcomes of accident statistics analysis

Data provided by the EUROSTAT database on accidents at work show that, if related to working population in the sector, rates do not decrease at all with time. In some countries the trends tend to be constant of show a slight decrease, but it is certain that despite legislative changes regarding safety and health and safety management fatalities will not be reduced fast in the upcoming years. This also shows that the agricultural sector does not follow overall statistics on health and safety since it is one of the most hazardous sectors and some of the hazards are part of the job.
Another conclusion can be drawn from those countries with a smaller rate of accidents at work per year: that given number of accidents per year can be seen as a background noise generated by sources of hazards that are not taken into account, like:

- Increase of possible negative outcomes involving machinery and its working environment;

- Wear-out of equipment, generating a constant flow of accidents related to poor or non-existing maintenance;
- Tight coupling among functions that are required to carry out agricultural activities when efficiency is required.

Further data analysis is provided in Appendix A, regarding data of every accident mode for every EU country in the period 2019-2018.

References

[1] E. database, “Accidents at work statistics (esaw),” *European Commission*, 2020.

Abstract

Safety is a key aspect in agriculture and the sector is one of the most dangerous among working activities. Machinery, environmental conditions and poor training are just some of the main aspects which negatively influence accident rates. It must be noted although that most of the time there is not a main cause of failure, it rather is a mix of reasons which might be harmless if taken singularly but that may lead to severe accidents if combined.

The complexity of the working context is not given by complex machinery or tasks, but it is strongly affected by the presence of harsh working conditions, lack of proper training and hazards that cannot be eliminated. To deal with this context, a dynamic approach to safety is required: a popular and relatively new analysis method called Functional Resonance Analysis Method (FRAM) offers a good way for handling dynamic scenarios and the efficiency-thoroughness trade off (ETTO) which is constantly present in a working environment. FRAM also aims to describe every scenario (including accident scenarios) as generated by output variability among the tasks that an activity is made of, so that there are no more cause-effect analysis only but instead internal and external variability (this is why it is described as "functional resonance" analysis method). This work aims to exploit FRAM's concepts to create a safety analysis method which is specific for agricultural contexts and that allows to identify performance-based safety solutions that prevent production losses and ensure safe operations. The AECAT cycle of analysis (accident analysis, effectiveness working mode, compliance ode, as-low-as-reasonably-possible mode and thoroughness working mode) has been created to manage the evolution of agricultural activities as external variables influence them (weather, soil conditions, market demands, time, etc).

Practical applications of this method include safety management tools and artificial intelligence (AI) algorithms which can enhance safety and reliability for specific machinery. Both those applications have been analysed and tested in this thesis and further research can be made to extend the range of possible solutions.

1 Introducing a "Competitive Safety" strategy to unlock hidden production potential

The aim of the thesis is to elaborate a performance-based safety analysis method for agriculture and make it feasible for both standalone applications on machinery and safety management systems. Efforts have been made to identify agricultural accident trends in Europe and, from data analysis, enhance an existing qualitative analysis method in order to make it work as a semi-quantitative safety analysis method in agriculture. The main aspects covered by this research covered the following aspects:

- The integration of safety and production in agriculture through new technologies;
- Comparison of quantitative safety analysis and dynamic approaches to safety;
- The development of a performance-based Safety management method for Agriculture;
- Highlight how the Functional Resonance Analysis Method (FRAM) has been employed to develop a specific method for agricultural activities;
- The role of Artificial Intelligence (AI) and Machine Learning (ML) applied to dynamic safety assessments.

These five aspects will be better described in the following paragraphs, and will be utterly covered in specific chapters.

1.1 Integrating safety and production in agriculture through new technologies

Agriculture and forestry are dangerous working sectors and they struggle every year with a high number of fatal accidents and long-term injuries. Victims sometimes even include bystanders, children and any other nearby persons, apart from workers. Conditions, working environment, hazardous machinery and solitary activities make safety management a complex task even for smallholding farmers. With the coming of smart devices and a large use of electronics in agricultural vehicles and equipment, agriculture became more

technological but hazards did not melt away at all. Mechanisation remains vital for farmers but poor interaction with somewhat harder-to-understand instruments and autonomous vehicles could eventually increase the chances of accidents with severe consequences.
In order to achieve better working conditions and to manage the typical risks of agriculture and forestry, safety must play a key role in design of future machinery. Its management needs to be embedded with quality at any stage and risk should be analysed from everyday performances rather than merely from accident statistics. Recent advances in Internet of Things (IoT) devices can greatly be beneficial to agricultural safety, since data and low-cost sensors can be integrated in agricultural machinery for cheap prices. At the same time, digital farming can be considered expensive by many, but would carry anyway additional benefits regarding safety. Given such scenarios, methods and models that are meant to manage risk in agriculture and forestry are needed and must exploit the possibility of doing so in a dynamic way, rather than statically or just simply by following cause-effect safety analysis methods.

1.2 Safety analysis in agriculture: quantitative safety analysis and human error rate predictions vs. dynamic approaches

Reliability analysis has developed many methods for risk prediction and failure rate estimations during the last 50 years. The need for such methods was required by safer designs for industrial plants that could have been prone to major accidents hazards and by applications in which safety played a mission-critical role (energy production, transportation, etc). The usual outcome of probabilistic reliability assessments (PRA) consists in a failure rate, or a combination of failure rates (fault tree analysis and event tree analysis) or a human error probability (HEPs): this kind of output requires basic events to be described as "working" or "failed", so it only accepts boolean inputs such zeros and ones, there is no space for fuzzy logic or other ways to describe the state of a component. These boolean events add up in a cause-effect way and can produce the probability for a certain accident (called top-event, because it is at the apex of a pyramid made of basic events that are combined together) and damage estimations.

This shows why Boolean algebra isn't always feasible in safety analysis of complex systems: since there are many different failure modes which also involve partial failures or latent failures, it can result in an model that doesn't properly describe reality as it is. Rather than just describing the component as "working" or "not working", a non-binary model should be implemented instead to keep anomalies into account and let predictive maintenance increase the system's reliability. It should be also kept in mind that non-technological variables and human performance can hardly be described as technological components that just work or fail, hence a more fitting model is required.

Many reliability analysis tools and methods such as Fault Tree Analysis (FTA), Event Tree Analysis (ETA), What-If, Failure Mode and Effect Analysis (FMEA), describe accidents that happen in a precise sequence or when certain system functions completely fail. Despite such methods can be of great help to define accident probabilities and provide quantitative safety analysis, they can hardly keep track of those common causes of failure (CCF) which might led many system components to fail all at once: some methods, like FTA and ETA (which together form the "bow-tie" model) also cannot describe components' failure modes and describe the system as a chain of boolean gates (AND, OR, XOR, etc). Such limits also affect any final probabilistic safety assessment (PSA) on the long run: such biases in calculating top event probabilities can, in fact, result in frequencies of occurrence that highly exceed those estimations.

For many reliability analysis tools and methods systems fail only following a cause-effect chain of component failures. Non-major anomalies which can add up and result in major accidents sometimes cannot even be taken into account since the status of a component can only be described in boolean terms. Ad described in Charles Perrow's book "Normal Accidents", accidents can be also provoked by a series of unfortunate issues which lead to major consequences even if they are, taken individually, absolutely not catastrophic events and rather just day-to-day contingencies. The book also shows how, describing investigations that followed the Three Mile Island nuclear power plant accident in 1979, how different analyses carried by companies and institutions led to completely different outcomes, almost all of them involving one specific cause that should be held responsible for the accident: from the example taken from real life, it was clear that every analyst missed the bigger picture of a complex system that can have a large variety of unexpected behaviours and an even greater number of unexpected outcomes.

Human behaviour is a key aspect in probabilistic safety analysis, in what literature used to define as human error and human error probability (HEP). Many analysis models such the Technique for Human Error Rate Prediction (THERP) and Cognitive Reliability and Error Analysis Method (CREAM) focused on identifying which tasks in a particular activity can be affected by human actions or behaviours. These approaches, although very useful for systems' probabilistic assessments, did not really take into account how human behaviour can also positively affect a system's outcome and fix any small anomaly before it could lead to failure: increasing a task's complexity results in greater numbers of unexpected outcomes and weighty decisions that, more often, must be taken in a short time. From this point of view entire accident analyses could be revised: if a complex system has a large number of unexpected behaviours which are unpredictable even at system design stage, then every human operator is responsible for its outcomes and should take merits for every small adjustments done in order to fulfil system's tasks.

From binary systems such FTA and ETA that are based on boolean logic, and above all from systems based on thresholds like many compliance regulations, new methodologies based on fuzzy logic must be implemented in order to cover every possible state in which a system's component can be found.

An important feature of many hazard and risk analysis methods is the capacity to look forward and detect accident scenarios that have never happened before but that are a real possibility. It is the case of Hazard and Operability Analysis (HazOp), but despite being one of the few methods doing so, scenarios only arise node by node and effects on other system's nodes are investigated step by step. Gathering information on latent failures, possible single-failure accident conditions and all those conditions which might lead to an accident scenarios is vital for safety system but such information often becomes clear only after they arise: the key aspect of safety analysis shouldn't be providing prevention and protection measures after an accident, it should instead foresee accident conditions and to do so analysts should look at those dangerous conditions which are present while a system actually works, instead of just looking at what went wrong and find counter-measures. This approach aims to search for latent accident causes or conditions that can generate danger even if, at first glance, tasks are getting done without issues.

Such methods, as mentioned, are all based on models which fail to properly describe those components and functions that cannot be assessed by boolean algebra. In addition, human error probabilities also fail to show when system's accidents are prevented by human intervention. To summarise, here is a list of the limits of those systems when applied to agriculture:

- Work as imagined by system designers strongly differs from work as done by operators;
- Elements involved in activities cannot be easily described as working or not working. There are anomalies and working modes that need to be taken into account as well;
- Workers can adjust their performance according to how an activity is carried out, meaning that they can also end up having little or no time for particular safety procedures or simply cannot put them into place;
- Cause-effect relationships are responsible only of a small part of common accidents. Many of them are, instead, related to more than simply one cause and result from several hazardous behaviours or working conditions that happen altogether and that might not be responsible of any accidents if they are present alone.

On the other hand, newer analysis method can offer a dynamic approach instead, overcoming the oversimplification operated by probabilistic risk assessment methods. The Functional Resonance Analysis Method (FRAM), for instance, allows a much more flexible analysis and a qualitative output for safety assessment. The aim of this work is provide a semi-quantitative approach instead, by upgrading the existing functional resonance analysis methodology and designing it for the needs of safety assessments in agricultural contexts.

1.3 A Performance-based Safety management method for Agriculture

Safety and Production has often been seen as dichotomous aspects of farming production since emphasis on the first can result in a decrease for the latter. This concept, on the other hand, is further strengthened by necessities on the field: good timing for harvesting, climate change and contingencies can endanger production and completely deny any profit, leading to sacrificing any other good practice and compliance that contributed to the business' growth. Despite a resilient and lean safety management can reduce the impact of adverse events, it is the first to be sacrificed to - temporary - reduce the expenses and gain faster production.

The first step to achieve better safety workplaces in agriculture must then require a new framework that allows safety to be embedded into production, a flexible instrument which creates the opportunity to adapt risk management to production management and understand the best strategies and solutions for every workplace and season. Performance-based safety management approaches are already known in fire protection engineering, because every measure is not defined by thresholds and requirements given by national regulations: they can adapt every solution based on what requires fire protection and by its value, therefore any solution is specific for a certain workplace.

Once achieved performance-based dynamic safety assessments it will also be possible to integrate new technology in order to obtain information from a distributed net of sensors on machinery and in the environment. This would allow workers to realise when hidden dangers arise and might help production by adopting the most effective solutions without renouncing to safety. Artificial intelligence (AI), for instance, can be of great help in classifying hazardous situations and latent internal or external performance variability, just as predictive maintenance does. Classification of thoroughness operations, compliance to regulations or need to achieve higher efficiency can be easily detected in single functions as in more complex activities if proper task analysis has been performed "a priori". Recent developments in AI increased its capabilities in detecting human behaviours as well, which makes it even more interesting for safety applications: nowadays, even top automotive manufacturers as Tesla Motors do not relay on radars and LIDARs anymore, but focuses on smart AI technologies that are able to detect obstacles with greater reliability.

An entire chapter will be dedicated to AI solutions applied to agricultural machinery for safety purposes.

1.4 A dynamic approach to safety: Functional Resonance Analysis Method (FRAM)

The Functional Resonance Analysis Method (FRAM) aims to describe an activity by its basic functions, which are linked by variables such as inputs, outputs, preconditions, resources, timing and control. Those parameters describe a function but not all of them must be specified for each one: preconditions, control and resources, for instance, might not be required for the execution of a specific task. The set of functions that are required to carry out an activity are called FRAM instantiations: since functions can be linked in many ways to each other to perform the activity, it would not be possible to describe all the possibilites in one figure because it rather shows the way it has been carried out in that moment. Functions utterly divide into background and foreground functions, while their flow in a FRAM instantiation defines them as upstream and downstream functions.
Each function has up to 6 parameters: inputs, outputs, preconditions, controls, timing and resources. These can be visualised as an hexagon as follows and parameters of a function will be linked to another function if a given output from a function takes part in another one.

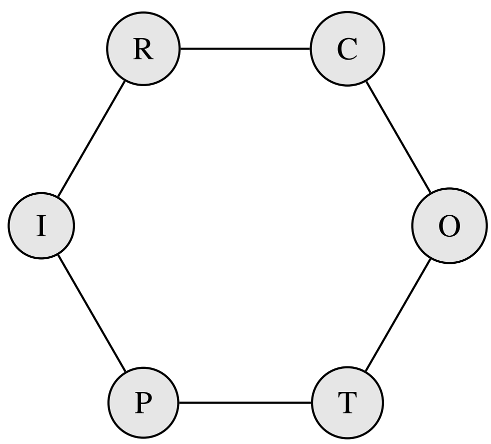


Figure 1: FRAM's graphical representation of a function

Those functions can be identified by Hierarchical Task Analysis (HTA) and links among functions may vary accordingly to how the activity is carried out every time.

Another important concept involved in FRAM functions is the ETTO principle. The whole FRAM is based, in fact, on the so called Efficiency-Thoroughness Trade-Off (ETTO principle) which refers to the inevitable trade-off between performing a certain task with precision and performing it as fast as possible to achieve the highest efficiency. If a task is carried out precisely, it will might result slow and not efficient: on the other hand, if the task is carried out fast, it might not be enough precise. The everyday activity for is affected by this trade-off and every small adjustment is based on the availability of time, resources and in the necessity (or possibility) to keep enough control on the outcomes or not.

The functional resonance analysis method will be further exploited to determine the most important instantiations, which are at least the following: accident scenarios, effectiveness working mode, compliance working mode, ALARP working mode and thoroughness working mode. Additional instantiations can be added in order to describe the ways in which an activity can be carried out in a dynamic way.

1.5 Artificial Intelligence (AI) and Machine Learning (ML) applied to safety assessment methods

A dynamic tool for safety management inevitably requires a large and reliable source of data, that can be provided by onboard sensors and environmental information from satellites, soil condition sensing and weather forecasts. Such data will also need to be handled and translated into valuable inputs for an algorithm that will assess the activities and establish what is needed to put into place to achieve a safe working environment.

Any kind of computer algorithm can be created to elaborate data and provide safety information: all those methods that include computer processing are called artificial intelligence. Most of the time it happens by hard-coding the ways that algorithms will have to produce alerts, signals, etc. This happens by setting thresholds, or by creating if-else statements for variables. Sometimes, although, the data flow is just too big and complex to be handled this way and tools which are more elastic are needed: machine learning and deep learning are, for instance, two important tools that can be exploited to create flexible algorithm that can adapt to any situation arising in working environments.

Machine learning algorithms can be implemented to detect internal variability in a FRAM function simply by detecting any variation in its components given a training dataset which helps to define what can increase it, what keeps it stable and what dampens it. On the other hand, further classification is needed to understand when a background function affects the system's variability, and link it to classify the task as performed at low or high resonance. It could also be used to better define qualitative risk analysis (low, medium and high risk) or to provide real-time information to workers as they perform their activities.

One of the most popular machine learning's algorithms is the Random Forest (RF), which is based on the generation of a fair quantity of decision trees made by picking a certain number of features (variables) inside a dataset and try to guess their relative label: the algorithm will try to predict the label by checking which one was the most predicted among the decision trees. The advantage is that RF can be trained with relatively small amount of data, for instance, even hundreds of rows are enough; on the other hand, although, every row in the dataset must be labelled and this is why such algorithms are called supervised since they must train on datasets which already contain the right answers (labels).

RF can do both classification and regression, so it can establish which label is the most appropriate for a row of data. It must be said that it cannot perform predictions outside its training dataset's domain: for example, if it gets trained on data like hourly wages (i.e. 20 € for 1 hour, 60 € for 3 hours, etc) it can predict wages inside its domain (for instance, it will predict 40 € for 2 working ours) but it won't be able to do so outside of its domain (it will predict the highest value, i.e. 60 €, even for an 8 hours shift).

Algorithms like random forests can be implemented to identify the proper FRAM instantiation in which a system falls for every moment of an activity. This can be done live, so that the algorithm might provide alerts to the workers through the machinery they use or on mobile phones. This will be further investigated in a specific chapter.

4 Resilience engineering applied to risk management

Since the first industrial revolution machines and systems required new safety regulations in order to protect the workers from harsh working conditions and hazards. At the same time, those machines became more complex and reliability engineering was born and quantitative safety assessment used to be carried out to define the probability of a system to be up and running for a certain amount of time. This kind of approach has always been oriented towards failure analysis, failure modes and causal links between an issue and its visible effects: in complex systems though, anomalies might also arise when everything seems to be working fine and such latent issues can play an important role in the occurrence of accidents, even if the final effect cannot be directly attributed to them.

All of that is resulting in a surge of interest in analysis methods which can be able to handle the bigger picture of safety management and exceed the reliability approach to describe systems with discrete or "fuzzy" logic that can be of great help in discovering why a system can fail even when none of its components can produce system failures by themselves. Even the human nature of workers can be analysed this way as a continuous trade-off between efficiency and thoroughness, which can often be strongly dependent by environmental, external or organisational reasons. From this starting point it can be possible to learn from mistakes, have better monitoring capabilities, identify latent failures and improve the chances of detecting and preventing accidents. A new analysis method of interest in this field is the Functional Resonance Analysis Method (FRAM) which aims to disassembly every function in a system and describe them on 6 parameters (Control, Resources, Input, Preconditions, Timing and Output) to determine how a sequence of change in the system variables can lead to changes in the overall performance.

FRAM instantiations can only consider a specific situation, like accident sequences. The graphical representation of them cannot serve as analysis tool outside of that specific system condition. To overcome such issue, FRAM method highlights the variability of each function in a system and aims to understand their impact on the system's resonance: that's why understanding function variability and effects on the whole system is crucial and represents a valuable resource for qualitative safety analyses. Having a qualitative assessment regarding certain instantiations, for instance on accident scenarios and safety-critical conditions, can although serve as the basis for an approach that aims to provide information regarding real-time status of a system. To do so, other working conditions (or state of the system) might be necessarily acquired: FRAM instantiations reporting activities carried out in compliance with regulations, alongside with other thoroughness-like conditions can help to draw the bigger picture of the most important operating conditions for a specific safety assessment. One of those instantiations which tend to be close to the most thorough way to carry out an activity can be identified in the As Low As Reasonably Possible (ALARP) condition. The ALARP principle states that risk shall be reduced as much as (practically) possible: practicality can be given by conditions in which investments in risk reduction still generate considerable benefits to the system's safety; a disproportion might result in a waste of economical resources with minimum gain on risk evaluations. Given this review of some of the most important working conditions that can be analysed altogether to get a wider representation of a system or activity's safety, those can be listed as follows:

- Accident instantiations, gathered from previous history or from an analysis of every possible negative scenario. Those conditions must serve as a lower threshold, indicating what must be completely avoided;
- Efficiency instantiations, that illustrate how an activity can be carried out in the fastest, or most economical, or most practical way, regardless of safety conditions. These scenarios are not dangerous by default, but can indeed be maintained only for a short time or in given certain background conditions in order to keep an acceptable level of safety;
- Compliance instantiations, intended as what must be done, and how it must be done, in order to consider the activity compliant with regulations and with instructions regarding how to employ specific equipment;
- ALARP instantiations, which refer to those activities whenever they can be carried out as thoroughly as possible until any economical effort to increase the system's safety would not generate a tangible overall risk reduction;
- Thorougness instantiations, that can often be referred as the most precise way to carry out an activity, regardless of its effectiveness, its costs or its practical aspects (ergonomics, timing, enforceability, etc).

These 5 conditions will later on be referred by their acronym as AECAT, indicating what has been taken into account as possible working scenarios when performing FRAM analyses.

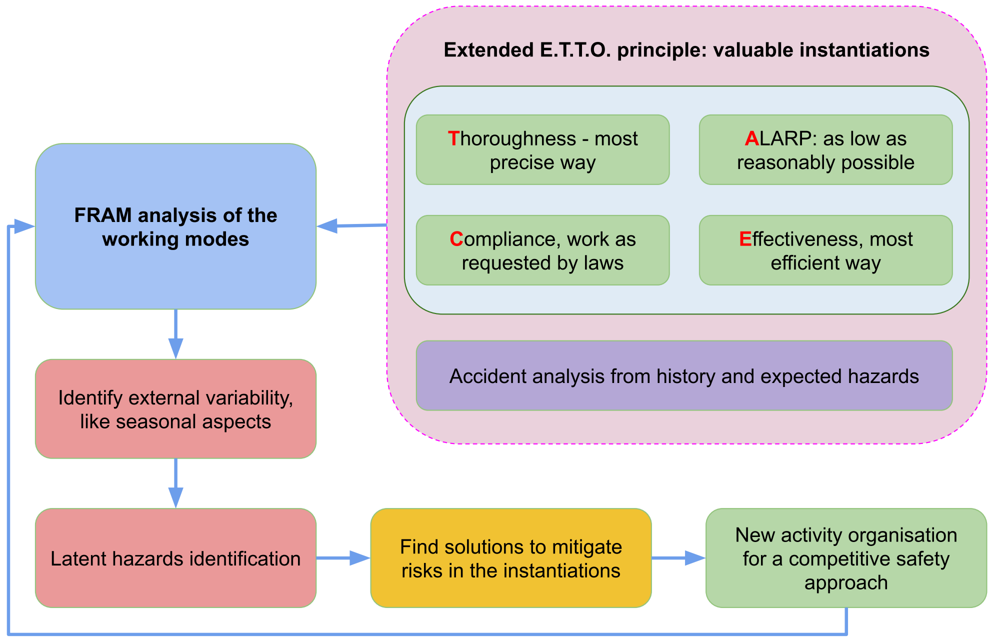


Figure 29: AECAT cycle

An analysis model has been created to highlight the advantages of this approach and to show what should be done at each FRAM stage of the process. The aim of identifying working modes is to understand not only the approximate or qualitative risk level of real-time activities: it can also help to identify any internal or external functional resonance and, at the same time, can determine which function couplings must be taken into account as possible source of resonance increase or dampening.

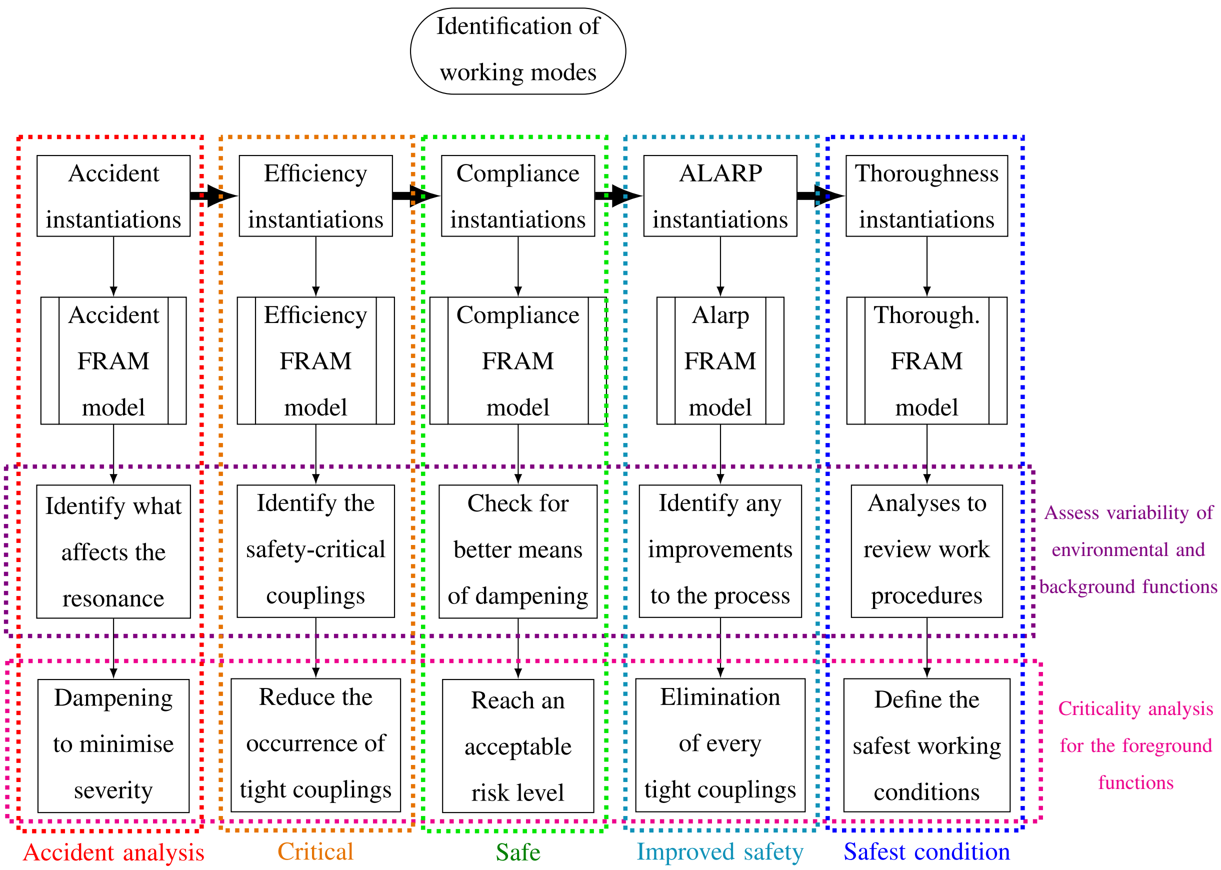


Figure 30: AECAT flow chart

Every step of the FRAM analyses shown in the previous figure help to understand a particular feature of the system/activity. For instance, accident analysis can be used to reduce the severity and understand variability thresholds that must not be exceeded; efficiency conditions might show the "tight couplings" among function that can generate an accident and, as a consequence, can indicate how to reduce their occurrence, leading to an acceptable risk level when better dampening means are into effect. This stage can be compared to compliance instantiations and understand whether the risk level will suffice or not: a narrow line might separate those two conditions but that is why ETTO principle indicates that activities are subject to small adjustments in order to be carried out, often finding a workaround that consents to fulfil a function's scope without affecting its safety in unacceptable way.

The result of FRAM analysis applied to AECAT working conditions is a series of considerations that can be drawn at several steps of the method. It can be summarised as follows:

- Variability can be assessed at both environmental level and background functions, providing an increasing degree of complexity as the functions that connect to form the activity instantiations become greater in number;
- Criticality analysis can be defined for foreground functions at every AECAT stage, allowing to determine which condition would be allowed or not at certain moments and when increased safety levels can be achieved with minimum efforts.

System's complexity plays, of course, an important role in translating AECAT FRAM analysis into practice. Activities in which workers control a vehicle to perform specific tasks can, in fact, be seen as a simple task since external variables are limited (but present) and the number of possible FRAM instantiations describing how the activity could be carried out are limited. Even a small number of functions can indeed be enough to describe the whole activity with a good degree of precision: this, although, is not always possible since other activities might be way more complex. For example, certain activities can be carried out by a wide number of possibilities involving even completely different activities, which must be analysed separately. These scenarios involve deeper context analysis and hidden couplings must be taken into account, especially because they might affect the transition from a safe to a dangerous operation. To summarise, the range of possibilities can be described as follows:

- Simple activities that can be represented as only one function are only affected by external variability and there would be no system resonance, intended as resonance transmitted by other functions that might generate a tight coupling inside the system;
- A system or activity which is made of few functions linearly linked can instead be affected by internal resonance that might propagate from upstream to downstream function, but still system's simplicity might allow only few different type of instantiations and thus making the job easier for safety analysts;
- More complex systems need to be assessed by identifying the most common instantiations first, and then integrating the analysis by searching for hidden couplings. Single points of failure (SPOFs) should be analysed in depth, not only by identifying cause-effect couplings but also by understanding and eventually finding any source of resonance that, propagating in the system/procedure, might cause them.

5 The FRAM into practice for agriculture

5.1 Fundamentals of FRAM

The Functional Resonance Analysis Method (FRAM) is a dynamic tool which can analyse scenarios and find safety issues by starting from how work is carried out rather than how accidents have happened. Additionally, it can highlight accident scenarios in a wider context by identifying the conditions which led to it: that method provides the possibility to describe accident sequences as they are, without the need to find any cause-effect relationships between any specific failures and the accident itself.
To do so, activities are broken down into specific tasks, or functions. These functions can be described as foreground or background functions, according to their role in the activity. Each function is described by 6 aspects:

- Input that starts the function;
- Output of the function;
- Preconditions that have to be present when the function starts;
- Resources needed to carry out the function;
- Time needed to run the function, or time at which the function must start or stop;
- Control that can be performed over the function as it runs.

Every function has an input and an output, the output of a function can feed any of the aspects of another function (except the output). The aim of the method is not to provide any graphical or schematic representation of the hazards in a certain activity, it is instead designed to describe instantiations of an activity that can be, for example, the work as imagined, work as done or accident scenarios. For specific instantiations, graphical representations are possible.
Given an activity, and having described its functions, analysis can be done by understanding how every output can vary. Any variation can generate no change in the downstream functions or, instead, generate positive or negative effects on the downstream functions. Missing or incorrect aspects inside a function, like its timing, missing resources or preconditions, can affect the output of the function itself. Such effect is called variability,

which can be external or internal.

The analysis of internal and external variability is paramount to identify the system's resonance under certain conditions. Resonance analysis allows to assess system's reliability in a qualitative way; it does not provide any numerical failure rate, but can identify which working modes are the most at risk.

As a result, phases of the analysis comprehend:

- Function breakdown;
- Accident analysis, in order to identify specific failure modes or single points of failure (SPOFs);
- Output variability analysis;
- Variability analysis.

Such method has been applied to agricultural activities, such as shredding. Results will be showed in the following subsections.

5.2 Case study: shredding activity

Activity analysis is the first step to carry out in order to define its functions. To do so, a Hierarchical Task Analysis has been carried out to understand how the activity works. Next figure shows its flow chart and will provide the basis for FRAM analysis.

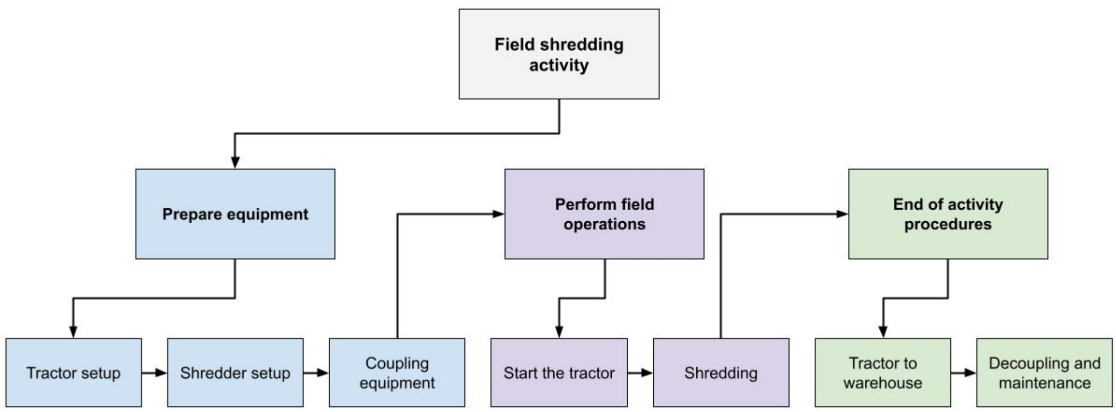


Figure 31: Hierarchical Task Analysis for shredding activities

Stop rules can be applied in order to limit the number of valuable functions that should be taken into account for the analysis. In this case, function "tractor to warehouse" can be ignored, since it doesn't involve any particular action or hazard.
Actions belong to three main activities, which are:

- Prepare the equipment and the tractor;
- Perform the activities on the field;
- Procedures that need to be carried out at the end of the activities.

Out of these main activities, 6 functions have been identified and can be listed as follows:

- Tractor setup;
- Equipment setup;
- Coupling tractor and equipment;
- Start and handle the tractor;
- Shredding;
- Decoupling tractor and equipment in order to perform maintenance.

Such activities will be deeply analysed as follows, in a way that fits the FRAM by describing their 6 variables.

5.2.1 Tractor setup

This function is designed to be, together with equipment setup, the first two actions that will be carried out in the activity. It might be carried out before, after, or at the same time of equipment setup, but it won't require any input anyway. It must be carried out precisely in order not to generate safety issues inside the function itself.

Function name: tractor setup	
Input	-
Output	Tractor ready for operations, ROPS enabled
Preconditions	Checklist from maintenance plans, safety procedures
Resources	Use and maintenance manuals
Control	-
Time	Performed before coupling starts

Table 7: Variables identifications for tractor setup

This function show why cause-effect relationships are not enough to describe accident scenarios. In order to carry out the function, workers might do it as prescribed by manuals and checklists, or might do it as they like, or might even skip it completely. This is not due to human errors, although: they might simply have no procedures for it, or maybe they never had the possibility to train on these actions required in the function, or manuals might be missing, etc. There is a large variety of reasons behind a missing action, or behind the so called human errors. The same pattern is present in many other functions as well.

5.2.2 Equipment setup

As for tractor setup, the way to carry out this function relies on resources availability (manuals, checklists) and available time. Together with tractor setup and coupling, this function is paramount to field operations.

Function name: equipment setup	
Input	-
Output	Equipment ready for operations
Preconditions	Check for any anomalies and prepare for coupling
Resources	Use and maintenance manuals
Control	-
Time	Performed before coupling starts

Table 8: Variables identifications for equipment setup

Output if this function is the coupling of equipment with the tractor, which is covered in a following function. It is clear that this function can be carried out in as many ways as tractor setup can be, and together can represent a reliable basis for further operations which would experience less anomalies. On the other hand, speeding up these functions (or not carrying them out at all) would result in anomalies later: this aspect will be covered in system variability analysis.

5.2.3 Coupling tractor and equipment

This function ends the preparations needed for field activities. It might represent a major source of hazards if carried out in the wrong way, as shown in the next table. It could, in fact, be seen as a source of internal variability (hazards generated while trying to produce the output) but, instead, it mostly affects the downstream functions.

Function name: coupling the tractor to the equipment	
Input	Tractor ready for operations
Output	Tractor and equipment are joined
Preconditions	Equipment ready for operations
Resources	Presence of a suitable ballast
Control	Tractor must be turned off
Time	-

Table 9: Variables identifications for coupling

From the previous table only one thing looks to be certain: this action cannot be skipped, delayed or postponed in any way because field operations would be impossible to carry out. Lots of variables are involved in this case and they represent how important this function can be for the shredding activity as a whole.

Some extra resources, such as manuals or checklists, have been voluntarily excluded because instructions regarding this action would already be included in the previous setup functions. Once missed, or once taken into account in the first two functions, outcome wouldn't change for this function as well.

5.2.4 Tractor handling

This function, together with field shredding function, provides the first moment in which environmental conditions such as weather, terrain slope, humidity or wind speed represent an external source of variability. Those background functions are the most challenging aspect of the FRAM applied to agricultural activities since, despite the background functions are quite the same in every instantiation, they might change rapidly and provoke adjustments in the day to day working practice.

Function name: tractor handling	
Input	Tractor and equipment are joined
Output	Start of shredding
Preconditions	ROPS enabled
Resources	-
Control	Terrain slope and other information
Time	-

Table 10: Variables identifications for tractor handling

The output of this function leads to the core function of the activity, so it should be where any previous resonance gets dampened. If it doesn't happen then the downstream function will experience issues in managing to achieve its goal.

5.2.5 Field shredding

As already said this function must take into account environmental variability from background functions. It also receives any resonance from the previous upstream functions (tractor setup, coupling and tractor handling) so it will eventually be the point in which accidents would happen the most. This is partially due to being the core of the activity, but its outcome will vary accordingly to how work has been performed before.

Function name: field shredding	
Input	Ready for field shreadding
Output	End of activity
Preconditions	-
Resources	-
Control	Terrain slope and other information
Time	-

Table 11: Variables identifications for field shredding

If the output of this function is achieved, then any previous issues regarding proper use of equipment and tractor will be dealt by the downstream function which should also prepare the machinery for next activity.

5.2.6 Tractor maintenance after the activities

This activity should be considered mandatory not only to keep the machinery operational, but also to be able to start working again in the next activity without much trouble. Maintenance, in fact, is measured as how much value the components will take back after intervention and it is also measured as mean time between failures (MTBF). During the time from failure and repair, the downtime will affect the production.

Function name: maintenance after the activities	
Input	Ready for field shreadding
Output	End of activity
Preconditions	-
Resources	-
Control	Terrain slope and other information
Time	-

Table 12: Variables identifications for maintenance

All the things that affect production can result in workarounds or at least need to take back lost time by saving time in other activities. This means that any issue that is not tackled by this function, will most likely appear again at machinery setup during the next activity.

5.3 Accident analysis

Accident analysis need to be provided not only from case-history, but also from the resonance point of view. Cause-effect scenarios that provoke accidents can be considered single point of failures, while FRAM also requires to examine how resonance can propagate through the system's functions for every hazardous variability.

Tractor handling	**Resonances**
Explosion of external hydraulic pipelines	Absence of maintenance for too long periods
Run-over	High speed, poor maintenance (visibility and brakes)
Impact against structures and plants	High speed, poor maintenance (visibility and brakes)
Overturning	Terrain slope not properly considered, high speed, wrong turning curvatures, wrong ballasts, ROPS not into place if present
Dragging	Anomalies during the activity that have been tackled with PTOs still active, tractor not turned off, maintenance most likely skipped before starting the activity
Electrocution	Contact of lifting equipment or other external components with power lines
Tractor setup	**Resonances**
Dragging	Operating with active PTOs, PTOs not properly protected, tractor not turned off, maintenance most likely skipped before starting the activity

Tractor handling	Resonances
Severe burns	Physical contact with power components or hydraulic pipes that have been used just before starting the activity, PPEs not in use
Run-over	Tractor not in stationary position or not turned off
Connection error of hydraulic pipelines	Wrong or absent identification of the pipes, procedures from the manual or training are not into place
Equipment setup	**Resonances**
Run-over	Equipment not in stationary position and absence of its stopping system
Connection error of hydraulic pipelines	Wrong or absent identification of the pipes, procedures from the manual or training are not into place
Overturning	Equipment not in stable position
Coupling	**Resonances**
Stability issues	Three point linkage not regulated
Overturning	Equipment and tractor not in stable positions
Dragging	Operating with active PTOs that are also probably not protected by carters, tractor not turned off, maintenance most likely skipped before starting the activity
Overturning	Equipment and tractor not in stable positions
Field shredding	**Resonances**
Dragging	Operating with active PTOs that are also probably not protected by carters, tractor not turned off, maintenance most likely skipped before starting the activity
Contact with active parts	Operating with active PTOs that are also probably not protected by carters, tractor not turned off, maintenance most likely skipped before starting the activity
Run-over	Equipment not in stationary position or not properly connected to the tractor, operations are too close to the end of the field provoking land subsidence

Tractor handling	**Resonances**
Ejection of objects from the shredder	Equipment not protected by carters and presence of by-standers or workers on foot
Maintenance at the end of the activities	**Resonances**
Safety systems not working properly	Makeshift devices in action when the right safety devices are not available
Run-over	Equipment not in stationary position
Dragging	Operating with active PTOs that are also probably not protected by carters, tractor not turned off, keys still in place
Severe burns	Physical contact with power components or hydraulic pipes, PPEs not in use

Table 13: Accident resonance analysis

Another type of variability can be provoked by external factors, such the environmental context or work management. In the following table some aspects are examined and their variability is taken into account for the related foreground functions.

Background function	**Description**
Manuals and procedures	Instructions to let workers perform certain activities in a proper way. Extremely useful for maintenance and equipment setup.
Position of the key	Keys must not be in ignition during certain activities
Correct ballast	An incorrect ballast would provoke issues in performing activities and safety-related issues regarding overturn accidents

Background function	Description
Environmental conditions	Environmental conditions can determine the speed, the moment and the way activities are carried out
Terrain conditions	Harsh or bad terrain conditions such as slope and humidity can represent a hazard for tractor drivers. Good terrain conditions can improve tractor's stability instead

Table 14: Background functions and their variability

Previous table shows how external variability is mostly caused by the working environment. Given that this pattern is present in many functions of the activity, it must be considered as major concern in safety analysis methods. FRAM is a tool that allows to see the big picture of working conditions in which danger arises from a mixture of reasons that, sometimes, cannot even be considered failures or negative events by themselves.

5.4 Internal and external variability analysis

As already stated at the beginning of this chapter, FRAM is about variability analysis. It is seen as the resonance that keeps propagating from a function to another, lining up a series of negative outputs from other functions and generating a tight coupling that might result in accidents even if every output, taken by itself, wouldn't be able to generate it.
It should be noted that a similar concept might be mistaken for parallel failures that only altogether can lead to a top-event in a fault tree, but it is not the case: those negative outcomes might not even be failures at all, they can simply be anomalies in outputs or missing parameters that do not prevent the outputs from working properly but might make things harder to fix later if other anomalies appear.
The following tables describes every variability and analyses its outcomes.

Function	Output	Possible output variabilities	Effects	Type of variability	Affected downstream coupling
Tractor setup	Tractor ready for operations, ROPS enabled	Timing: omission	V+	External	Coupling (input)
		Duration: too short	V+	External	Shredding
		Object: wrong action	V+	External	Tractor handling (precondition)
Equipment setup	Equipment ready for operations	Timing: omission	V+	External	Coupling (input)
		Duration: too short	V+	External	Shredding
		Object: wrong action	V+	External	Shredding
Coupling	Tractor and equipment are joined	Speed: too fast	V+	External	Tractor handling and field shredding
		Object: wrong action	V+	External	Tractor handling (input)
		Sequence: reversal	V+	Internal	
		Sequence: correct and check for wrong actions	V-	Internal	

Function	Output	Possible output variabilities	Effects	Type of variability	Affected downstream coupling
Tractor handling	Start of shredding	Speed: too fast	V+	Internal	
		Speed: too slow	V-	Internal	
		Object: wrong action	V+	Internal	
		Sequence: reversal	V+	Internal	
		Direction: wrong direction	V+	Internal	
Field shredding	End of activity	Speed: too fast	V+	Internal	
		Speed: too slow	V-	Internal	
		Force: too much	V+	Internal	
		Force: too little	V+	Internal	
Final maintenance	Tractor is ready for a new activity	Timing: omission	V+	External	Tractor setup (resources)
		Object: wrong action	V+	External	Tractor setup (resources)

Table 15: Output variability - foreground functions

Background function	Output	Possible output variabilities	Effects	Type of variability	Affected downstream coupling
Manuals and procedures	Checklists	Object: wrong object	V+	External	Prepare tractor, Prepare equipment
	Manuals	Object: wrong object	V+	External	Prepare tractor, Prepare equipment
Position of the key	Key not in ignition	Timing: omission	V+	External	Coupling
Correct ballast	Ballast ready	Object: wrong object	V+	External	Coupling
Environmental conditions	Weather condtions	Timing: too late	V+	External	Field shredding
Terrain conditions	Slope and humidity	Timing: too early	V+	External	Field shredding

Table 16: Output variability - background functions

5.5 AECAT working modes identification

In the previous chapter an analysis model has been provided to further assess FRAM outcomes, based on working modes that can be identified as:

- Accident analysis;
- Efficiency mode;
- Compliance mode;
- ALARP mode, as low as reasonably possible;
- Thoroughness mode.

These working modes are an application of the Efficiency-Thoroughness (ETTO) principle. Given that list of working modes to be explored, graphical FRAM instantiations for each of them has been generated.
It is worth remembering that more working modes can be added to the model, accordingly to the type of activity. For instance, an activity might be performed in a way that is compliant to regulations but that is not yet falling in the ALARP mode, so additional states must be added; or again, there might be other working conditions between compliance and efficiency mode.
The main characteristic of the AECAT model is that foreground functions are always connected in the same way because the hierarchical task analysis(HTA) always identifies the same workflow. Such model, that can be implemented only because of that HTA outcome, allows to properly assess the impact of background functions: these functions, like environmental conditions and organisational variables, play a key role in the whole safety assessment of agricultural activities.
The first graphical representation shows how shredding activities should be carried out in a thorough way. Functions have all been already well described, and every hexagon contains information regarding the functions' own parameters (input, output, control, timing, preconditions and resources). They are connected where the output of one is involved as a parameter of another function. Red circles around a parameter indicates that it is needed, but not provided by another function: it is like the resource parameter "fuel" for machinery, which is required but not provided by any of the other functions in the instantiation.

Rules can be established in order to know where to stop, and discard some parameters that play no significant role in the activity as a whole and that are not involved in any way in internal or external variability.

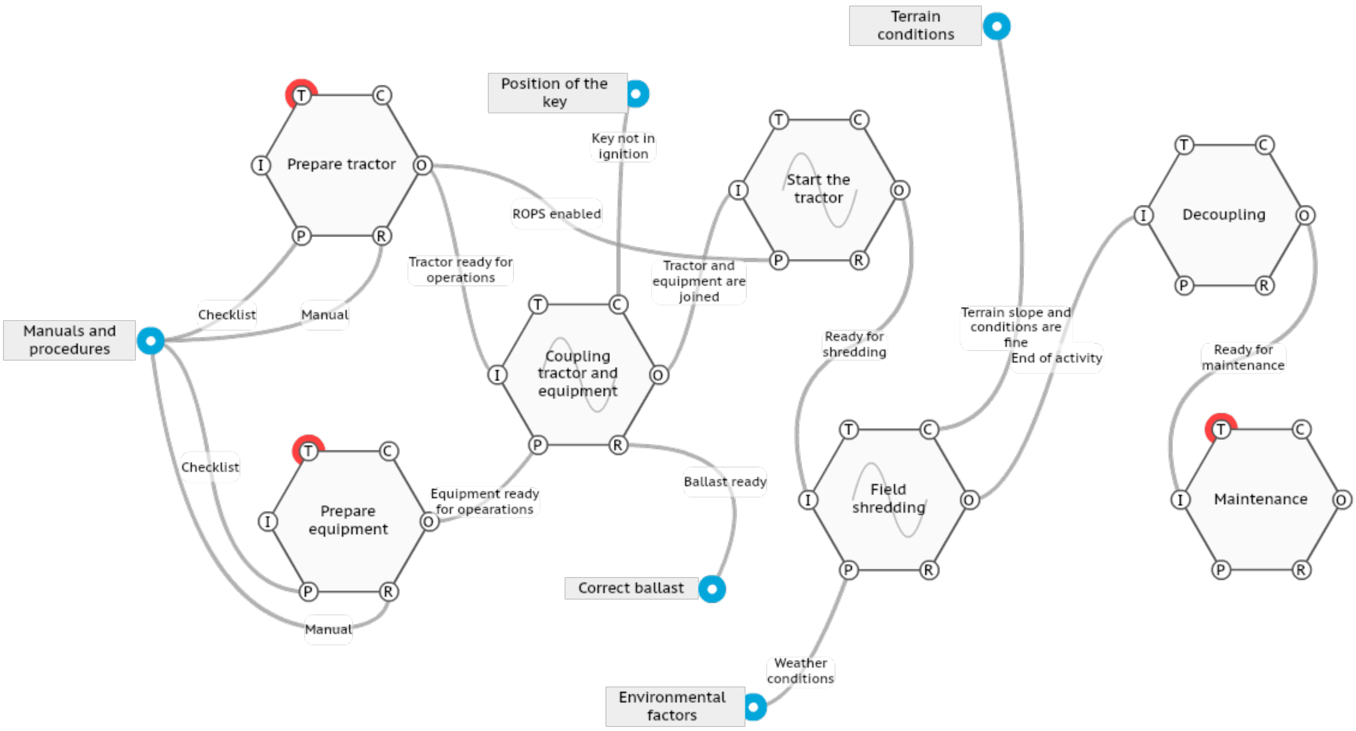


Figure 32: Shredding activity - thoroughness mode

Thoroughness mode is the most complete among AECAT instantiations. From now on, other working modes will be identified by removing some of the requirements (links) that are present in that representation. For instance, terrain conditions represents an important parameter in that case but an activity, in real world, might need to be carried out anyway: so, in the ALARP working modes, it would no more play as "control" parameter in the field shredding function. This is the only difference among thoroughness mode and ALARP working mode for the analysed activity, but scenarios might greatly differ in other cases. The outcome of losing information regarding terrain conditions loses a dampening effect inside the field shredding function: since the function is indicated by a sinusoidal symbol inside its hexagon, it means that its output can be affected by some sort of variability that should be managed and kept under control. This is why ALARP working mode is inherently less safer than the thoroughness mode scenario.

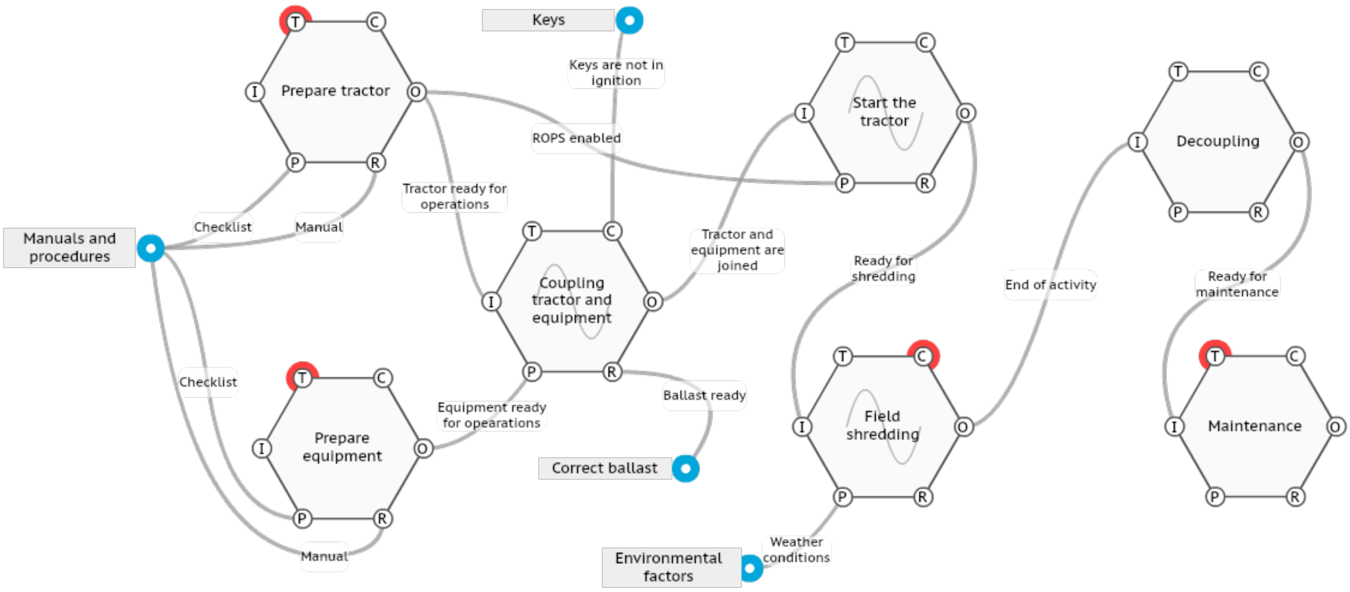


Figure 33: Shredding activity - ALARP mode

As already explained, ALARP working mode is very similar to the thoroughness working mode, except for the missing terrain condition parameter which was meant to control the shredding function. Another parameter that is present in that instantiation but that is not required by any regulation is weather conditions: the presence of rain might prevent the activity from being carried out, but strong winds, for instance, would not do the same. That is why the background function regarding weather is the most important parameter that makes this working mode differ from compliance working mode.

No other significant change seems to be required to skip from this working mode to compliance working mode. The compliance working mode requires only what is requested by regulations to carry out a particular activity, this is why some background functions are not influencing the workflow in any way: this is the biggest work-as-imagined difference from work-as-done in agricultural environments, since these background functions instead influence a lot the whole activity and might even prevent it from generating any profitable outcome.

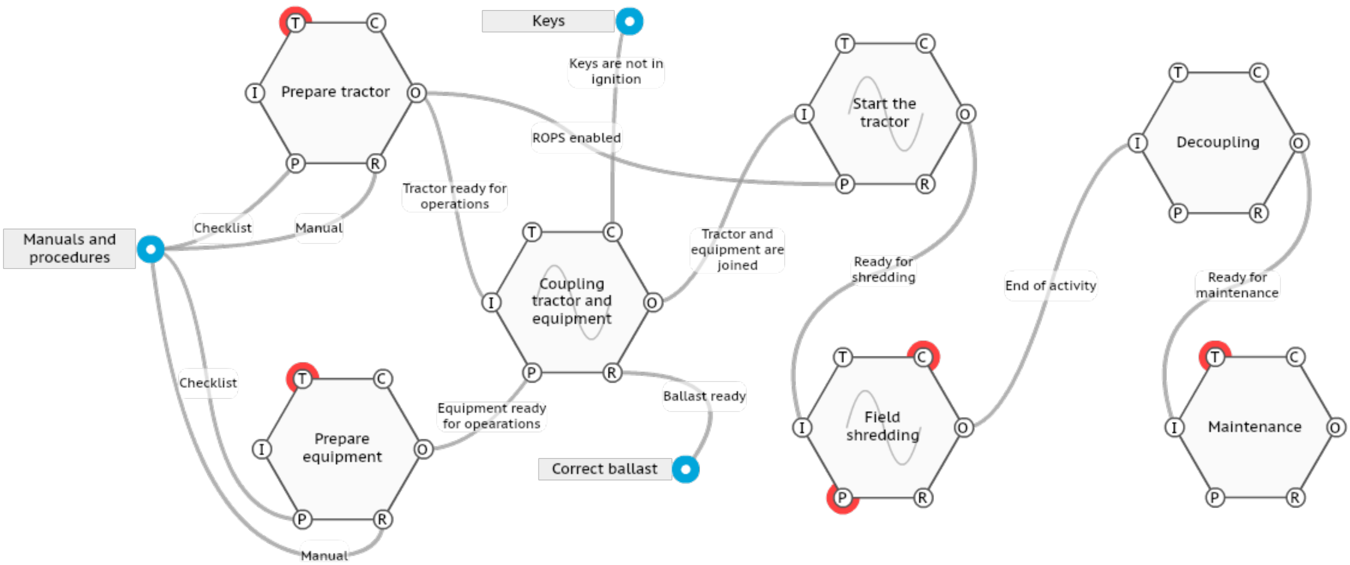


Figure 34: Shredding activity - compliance mode

The previous figure shows a graphical instantiation for compliance working mode. Despite it can theoretically be seen as minimum requirements scenarios, several other working modes can be possible from there to the effectiveness working mode. This is why performance-based safety management can represent a valuable resource in shaping prevention and protections systems: another great value is represented by the possibility to base the whole activity management on that performance-based safety solution that has been identified with this method, enabling the coupling of performances to safety means.

In order to reach the effectiveness working mode, several links have to be removed from the compliance working mode. Maintenance would be performed as workers intend to do without following any checklist or manual, and machinery coupling will follow the same pattern (tractor might be turned on during activities which require it not to be in ignition). Rollover protective system (ROPS). if present, might not be in place and ballast size might not have been properly checked. These conditions can lead to accidents more rapidly than other working modes, but on the other hand carrying out the activity would require less time: that is why barriers get often removed during certain activities and that is also why tight couplings happen, since there are no ways to dampen any kind of internal or external variability.

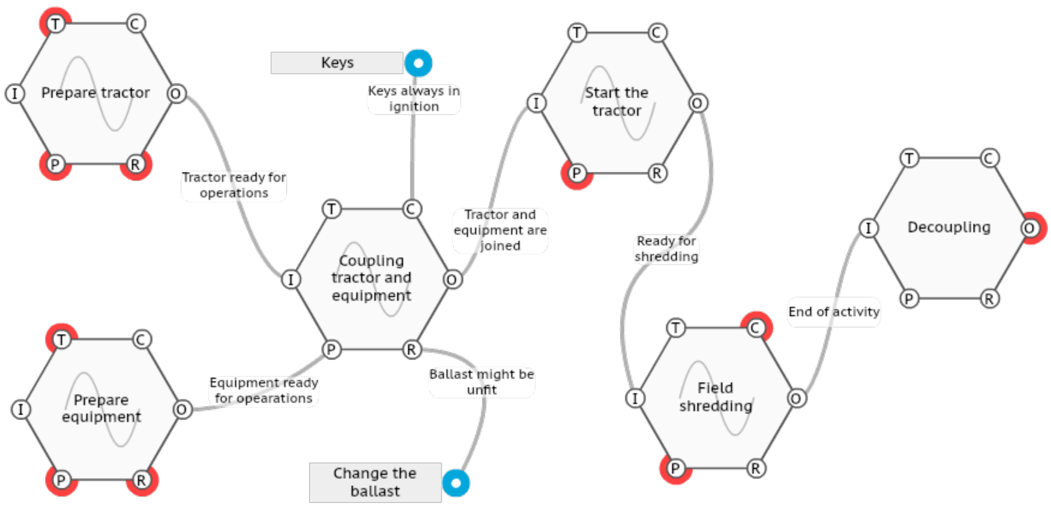


Figure 35: Shredding activity - effectiveness mode

Despite being often dangerous, such effectiveness working mode can be adjusted in a way that might be considered acceptable for a short time. This must be done by including additional functions that are meant to dampen the expected resonance of the system. Such dampening effects would be designed to avoid losing time and resources, with the aim to increase system's safety at least to the expected levels of compliance working modes.

Working mode switch	**Changes**
From thoroughness to ALARP	No terrain conditions data
From ALARP to compliance	No environmental conditions data
From compliance to effectiveness	Not following any manual or checklist, safety devices disabled (ROPS)

Table 17: Summary of changes among working modes

At the end of an oversimplified analysis, it is already clear that the most important sources of resonance are external to the system. This should not be seen, although, as a source of hazard: weather, terrain conditions, barriers, are rarely responsible of accidents but any misunderstanding on their impact (or absence) can lead to severe consequences.
Some of the background functions responsible of switching among working modes produce hazardous effects not just on the function they are linked to but also on other downstream functions. This is the effect of resonance on the system, since issues that involve an upstream function show their effects on a downstream function. It cannot be identified as a domino effect, since the upstream function might even show no anomalies at all but just hazardous variability on its output.
This FRAM analysis can serve as starting point for additional safety analysis involving, for instance, the identification of any suitable dampening effect for every scenario that might need enhancements to be at least as safe as the compliance mode scenario.
From another point of view, those background functions might be monitored inside of a foreground function: this will be covered in the next chapter involving sensors and artificial intelligence on modern tractors.

6 Enhancing the sensors: artificial intelligence for anomaly detection

The increasing availability of data, both from machinery and from external sources (geospatial information, detailed weather conditions, etc.) provides researchers with the opportunity to study and develop newer systems, based on artificial intelligence algorithms like deep learning or machine learning, which can now rely on better and extremely fast hardware. Some algorithms in fact already existed before and mathematical theory behind them has been developed fifty or even a hundred years ago but they never had the opportunity to run as fast as they needed on the microcontroller units like those we can exploit today and that we can get very easily without spending too much. There are three main development activities related to machine learning and artificial intelligence which can enhance safety management of machines, systems and workplaces: - Identification of performance variability, which are needed to identify any issues during the execution of single tasks that can be generated by any lack on control, resources, inputs, preconditions or timing and that alter the output of the task/function. Another kind of variability can also be due to external conditions, like organizational requirements or environmental causes; - Anomaly detection, that can be performed on human behaviours or variables to detect abnormal values through isolation forests or autoencoders which don't need examples of the selected abnormal cases to train the algorithms since they just recognise them among other cases as the values can look different and singular from normal cases; - Machine Learning (ML) classifier for risk assessment, which allow to assess a specific situation as low, medium or high risk. This can also be done for events in the imminent future and identify a raise of risk level (i.e., a vehicle moving towards a high slope terrain and might run into lateral overturning or backward rollover).

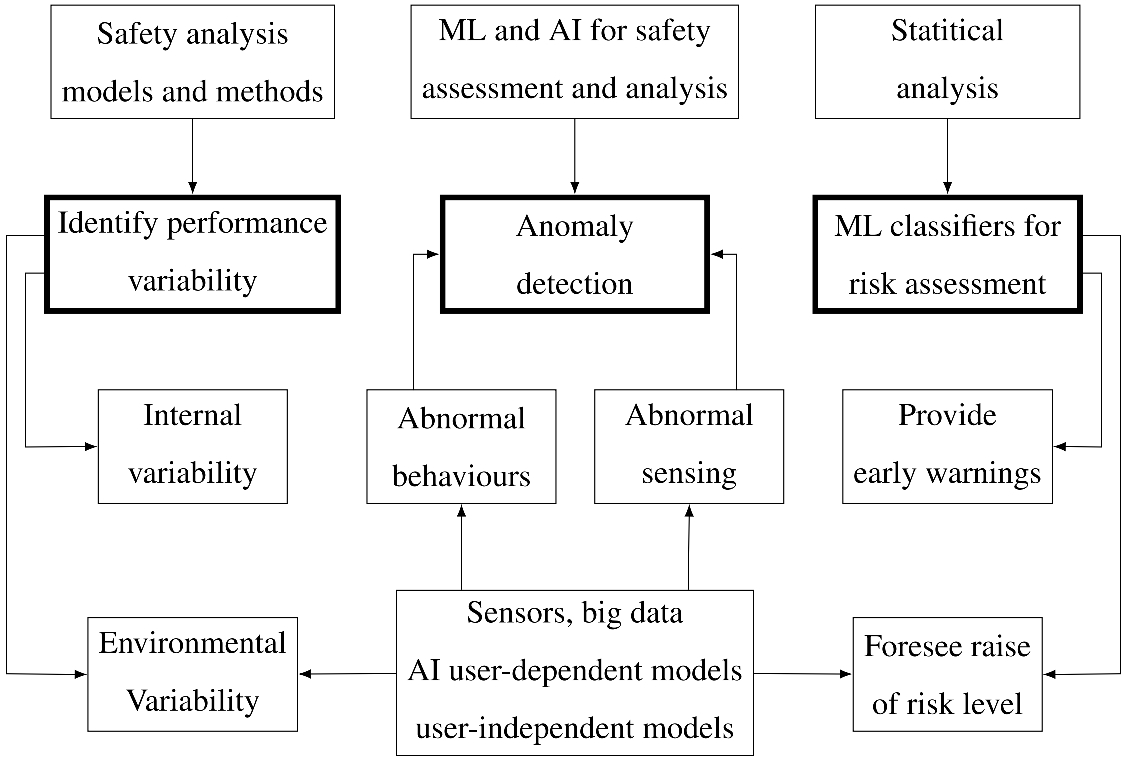


Figure 36: Interactions among safety analysis models and AI for new assessment tools

All of that requires data from sensors, or big data from external platforms or a mix of these which can allow to define user-dependent models (in which anomaly detection can be adjusted to the user) and user-independent models (a mixture of user-dependent and user-independent models is yet a possibility if enough data is available). The identification of performance variability relies instead on existing methods and models for safety analysis, which are mandatory to read any efficiency-thoroughness trade-offs as they happen and as they become too dangerous. Last but not least, it must be underlined that any Artificial Intelligence algorithm (as machine learning, neural networks or deep learning) require the usage of mathematical and statistical tools in order to perform a fine tuning of their performances.

7 Machine learning for risk analysis in agriculture

7.1 A case-study on tractor stability based on functional resonance analysis

Agricultural and forestry activities represent a challenge for occupational safety and health management due to dangerous working conditions, equipment that needs to be handled properly and a series of environmental aspects like market demand, labour costs and climate change uncertainties. Given such a background, any investment for safer working conditions must go hand in hand with product/service quality and should not be justified by law compliance alone. To achieve an acceptable level of risk a variety of analysis methods could be taken from well-known industrial experience, but there are macroscopic differences among the sectors which make the whole system to be considered as intractable: lack of data, incomplete information about how hazardous scenarios arise, environmental unstable variables and a strong interdependence between activities and background conditions. Another important aspect, apart from root or single causes of accidents, is the need to extend the analysis to those latent or hidden anomalies which can altogether be responsible of an accident: it would be impossible to rely only on accident history or to describe every element by using only two states (state of working or state of failure) and even more critical would be the definition of formulas meant to detect hazardous working conditions since the model wouldn't easily fit to reality. A newer concept based on resilience engineering should instead be considered in order to:

- Define the state of components with fuzzy logic
- Consider any small or hidden changes of one (or more) variable(s) which may affect the whole system's safety
- Manage an efficiency-thoroughness trade-off

This approach can be found in the Functional Resonance Analysis Method (FRAM)[1] which mainly aims to describe every basic function of a system by its inputs, outputs, preconditions, controls, resources and timings needed to be carried out; from any variation of a function's variable a resonance could be produced (or not produced), and it extends to its downstream functions which can be affected by it. Even some dampening of an existing resonance might happen, reducing this why the risks derived by system instability. The method can this way describe any instantiation of the system whether it is working or not. This means on the other hand that a risk quantification might be a hard task to perform since every change in the system might affect its resonance and the risk assessment of that specific instantiation. In the following figure, a simplified description of the activities which can be carried out to perform mechanical pruning is described, indicating:

- Every function with a hexagon made by its Control, Resources, Inputs, Preconditions, Timings and Outputs;
- A different colour for every type of functions (human, technological, etc);
- Links to show how every function relate to each other;
- Labels to describe the meaning of the links;
- A symbol of a sinusoid inside functions to indicate if they might affect system's resonance or not.

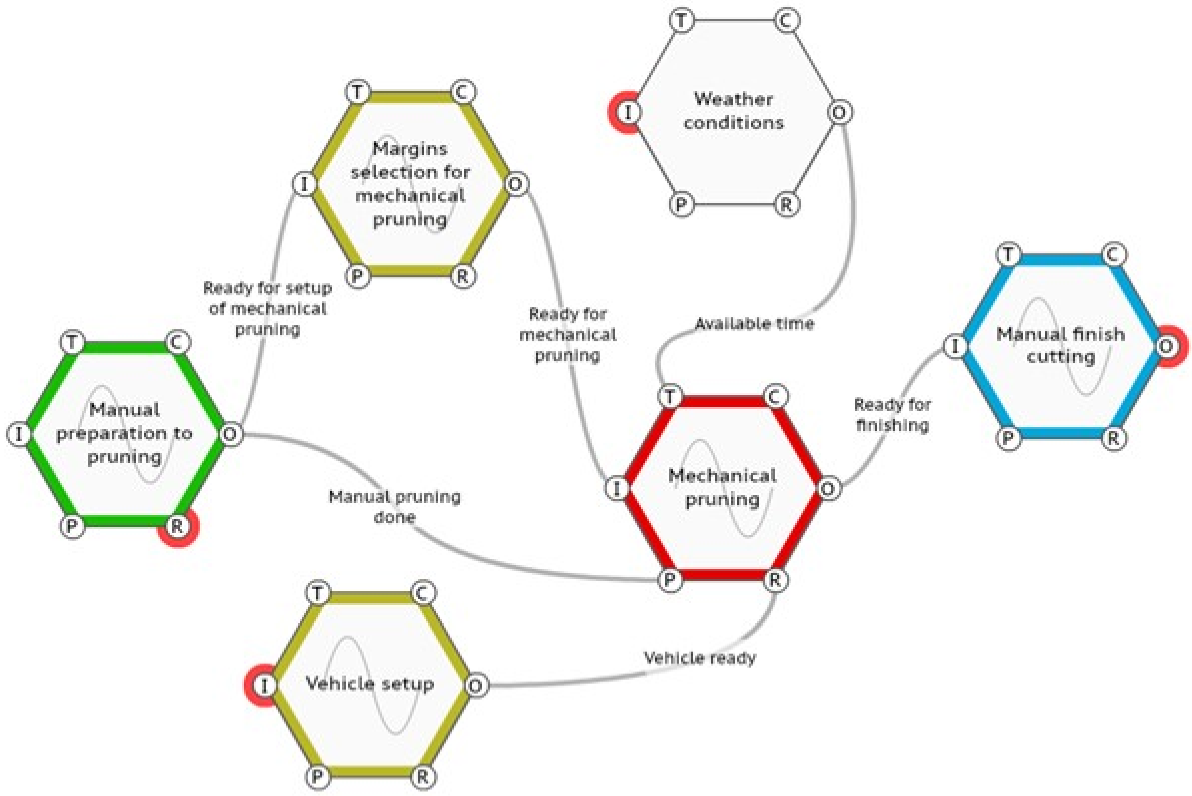


Figure 37: example of FRAM model for mechanical pruning

The previous figure shows how FRAM can describe the expected outcomes of every function and can be done even to describe accidents by showing which variable(s) affected the final outcome. Further development of the method can include a quantitative risk analysis based on internal or external resonances among the functions. This might be done by analysing enough data from a certain system and by identifying hidden anomalies which might not lead to any immediate issue but might do so later in combination with another one: a Machine Learning algorithm can be of great help in detecting such hazardous working conditions.

7.2 Case study: qualitative risk analysis of tractor stability

One of the principal risks in agriculture is related to tractor overturns, which can be due to a large number of aspects and might lead to severe or fatal consequences if all the individual protection devices have not been put to work. The main goal is to achieve a reasonable safety level by prevention, which means removing sources of danger or reducing their impact on the system. To do so, a FRAM model has been defined to identify which of the functions related to the use of a tractor can affect rollover probabilities: as a result, despite many causes can be found inside the function itself, some of them depend by external working conditions (environment, weather, type of activity, etc).

Figure 38: basic FRAM model for safety-related functions involved in tractor usage which can affect rollover probabilities

From the activities shown in figure 2, a set of system variables has been selected to investigate how they can generate low, medium or high risk of rollover. Such variables are:

- Internal:
  - the tractor;
  - Sequences (the way the driver should manoeuvre the vehicle);
  - Curvature angles while turning;
  - Type of activity performed on the field;

- External:
  - Weather;
  - Timings;
  - Slope;
  - Humidity and soil stability.

From those 8 variables a dataset of 500 entries has been developed. Every value has been defined by an index which spans from 1 to 10, except for activities (which go from 1 to 5) and timing (which has only 3 values: 1 for short period, 2 for normal and 3 for long periods of activity). Minimum and maximum values would then correspond to the minimum and maximum achievable values for every specific measurement. For every entry a rollover risk level has been manually assessed based on experience. The labels for risk are 1 for low risk, 2 for medium risk and 3 for high risk. Starting from that dataset, 80 percent of the entries have been randomly picked for a Random Forest machine learning algorithm[2], while the remaining 20 percent have been set apart for testing purposes.
As a result of the random forest algorithm training, some conclusions can be drawn on the importance of every variable for the final risk level prediction. As obvious the most important variables are speed of the vehicle and terrain slope, followed by the manoeuvring and curvatures made by the driver. A certain impact is given from status of the terrain and weather forecasts, while less importance has been given to type of activity and duration of the activity, as shown in figure 3.

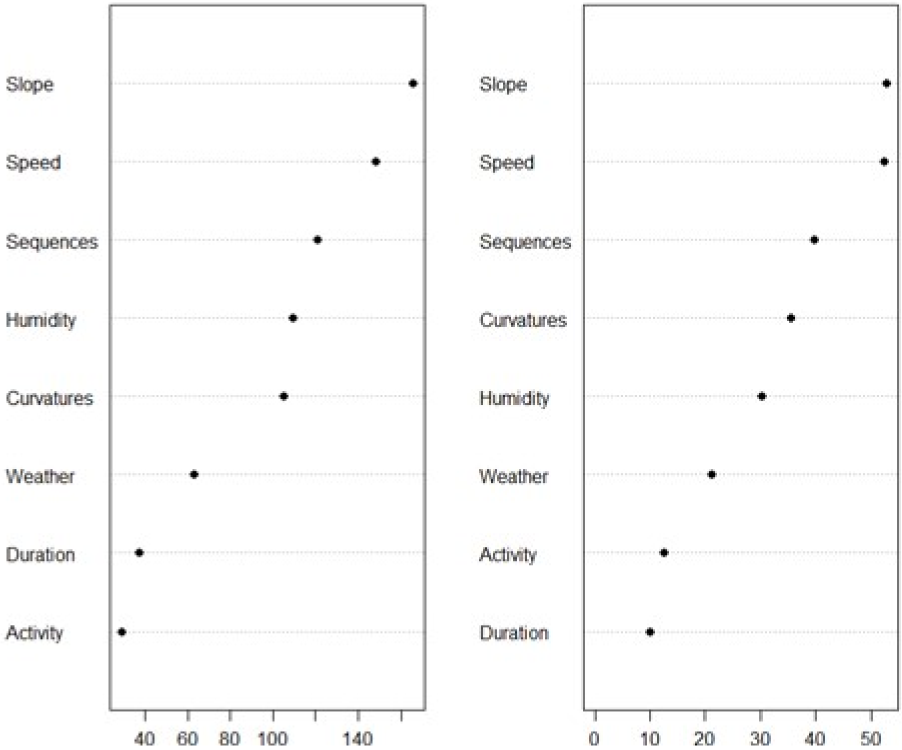


Figure 39: mean decrease accuracy and mean decrease Gini for the Random Forest

The values shown in figure 3 are intended to be an estimation of the importance of the variables within the dataset: this is due to the large number of very safe or highly unsafe entries which do not depend by their type of activity or by their duration in any way. More analyses can be performed on the dataset, before checking its reliability by doing predictions on the test set based on what has been learnt on the training set. As shown below, Euclidean distances and 3D distances can be plotted to show homogeneous values in the dataset.

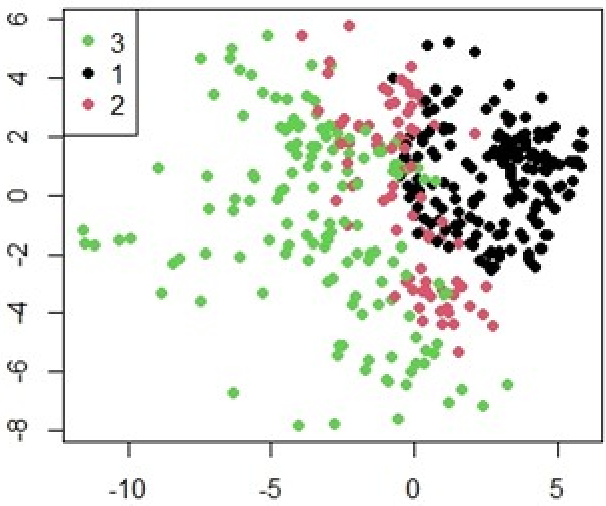


Figure 40: euclidean feature distances

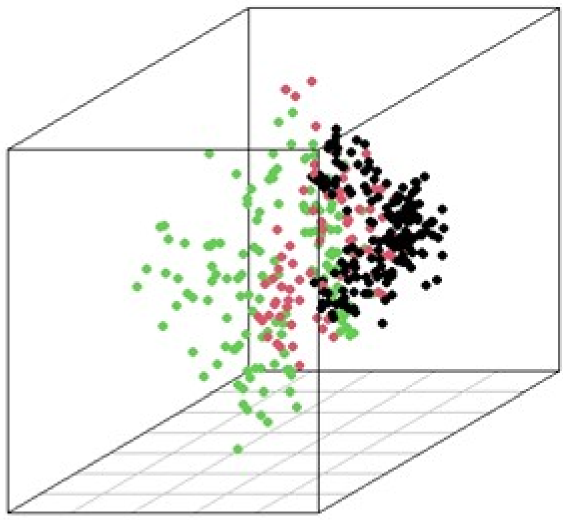


Figure 41: 3D feature distances

From figures 4 and 5 is it clear that some points of the dataset have been labelled as 1 (low risk) but are shown within close distances from entries labelled as 2 (medium risk). Same goes for many medium risk entries which appear in the high-risk area, labelled as 3. This is due to particular conditions affecting tractor stability and demonstrate that a classifier algorithm couldn't be hard-coded for this case-study, and that a machine learning algorithm could provide better predictions.

As a result of training a random forest algorithm with 3000 trees of 3 nodes, an Out of

Bag error (OBB) of about 4-7 percent has been obtained. Predictions on test database (20 percent of the base dataset, 100 entries) showed at least 96 percent of correct predictions, 2 percent of predictions which reported lower risks classified as higher, while the remaining 2 percent of predictions involved higher risks shown as lower risks levels (table 1).

Prediction	Label 1 (low risk)	Label 2 (medium risk)	Label 3 (high risk)
Predicted as “Label 1”	50	2	0
Predicted as “Label 2”	0	10	0
Predicted as “Label 3”	1	1	36

Table 18: algorithm predictions on the test dataset.

Further analysis could take into account the “voting” which resulted in every label prediction: average results could be calculated (for example 60 percent label “3” and 40 percent label “2” would result in 0.60*3+0.40*2, so it would be 2.6 with an error of 0.4 if correct value is label 3, or 0.6 of the correct label is 2).

7.3 FRAM-based machine learning for risk assessment

To increase the detectability of anomalies and the reliability of a machine learning algorithm for risk assessment, internal and external resonances can be analysed separately. First of all, it must be recalled from what has been described before that some of the variables can be considered as external sources of resonance since they belong to background functions from figure 2, while others are specific of the main “blue function” related to the usage of the tractor itself. From that classification there can be 4 different labels for their impact on system’s stability:

- Label 1: low resonance and low risk. A dampening effect can also be noticed since such conditions even reduce the overall risk conditions of the system;
- Label 2: low risk, doesn’t dampen nor increases the overall resonance of the system;

- Label 3: low/medium risk, indicates a status which can be sustained without any major safety concerns but only due to an internal dampening of the function;
- Label 4: high resonance, tendency to medium or high risk.

A comparison with the previous example might show an increase in the number of classifiers, which are now 4 instead of 3. But for these classifiers less variables are needed and results can be more precise and faster.
The dataset's column used for this machine learning algorithm are only “weather”, “slope” and “humidity”, plus a label column which has been manually estimated in order to let the learning process begin. Some words can be spent again on the homogeneity of the dataset which looks quite simple in the following figures 6 and 7. Some differences within a label is still present, like in figure 6 for the Label 3 (green) which looks divided in two far groups.

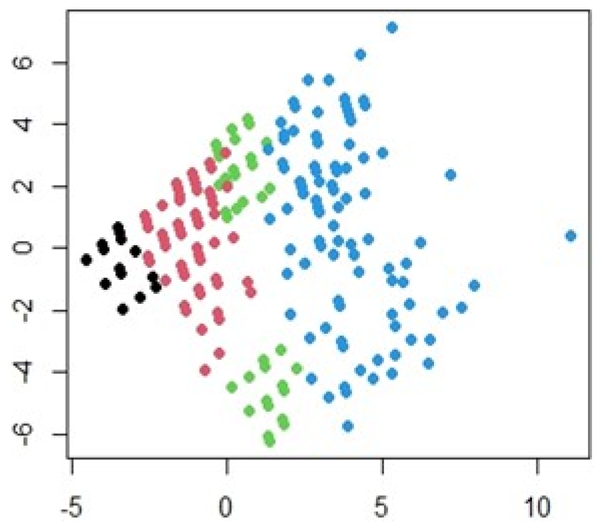


Figure 42: New euclidean feature distances

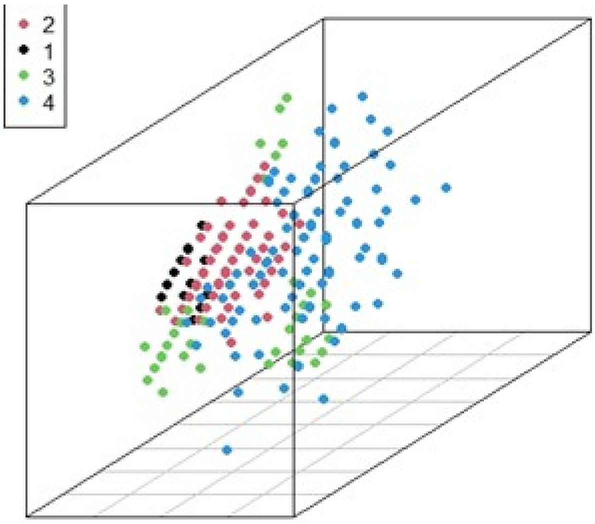


Figure 43: New 3D feature distances

Learning parameters have been left identical from the previous test, using 80 percent of the dataset for training (400 rows) and 20 percent for testing (100 rows). OBB error for this learning process has been lower than 3 erpcent, and as a result the algorithm managed to predict the 97 percent of correct results, zero percent has been predicted as a higher label and 3 percent as lower label.

Prediction	Label 1	Label 2	Label 3	Label 4
Predicted as “Label 1”	20	1	0	0
Predicted as “Label 2”	0	34	1	0
Predicted as “Label 3”	0	0	13	1
Predicted as “Label 4”	0	0	0	30

Table 19: prediction results for external system resonance

Another set of 4 variables (activity, curvatures, speed and sequences) has been identified as responsible of internal resonance in the main function of the FRAM scheme. Even for this case the same set of labels has been used and models to understand feature distances has been developed.

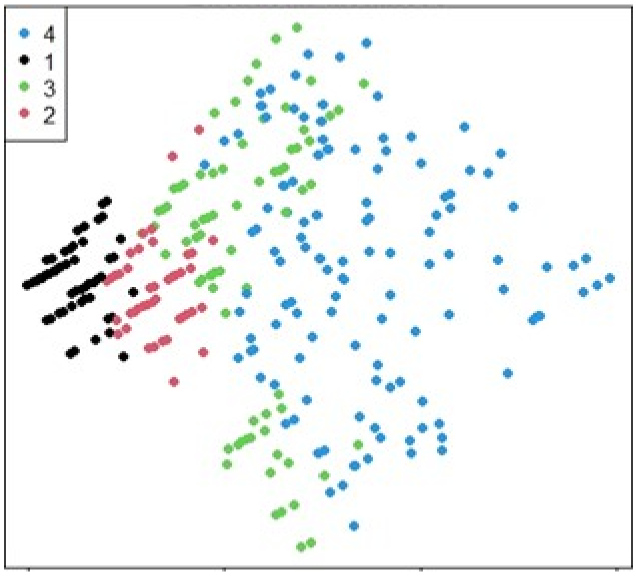


Figure 44: Euclidean feature distance in tractor activity function

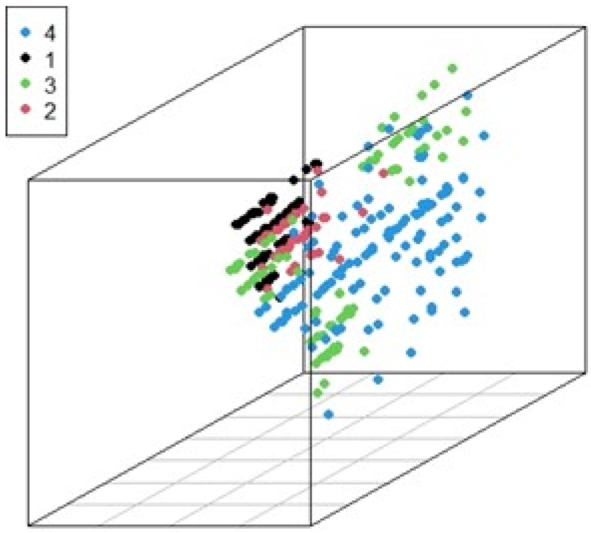


Figure 45: 3D feature distance in tractor activity function

Figure 9 shows again homogeneity among features but figure 10 is less clear. From this point of view the solution of splitting functional resonances in different algorithms seems to pay off. The OBB for this training algorithm has generally been lower than 5 percent, giving 98 percent of correct results, while predicting a higher label in 2 percent of cases and a no lower labels (0 percent of the cases).

Prediction	Label 1	Label 2	Label 3	Label 4
Predicted as “Label 1”	20	0	0	0
Predicted as “Label 2”	1	12	0	0
Predicted as “Label 3”	0	0	24	0
Predicted as “Label 4”	0	0	1	42

Table 20: prediction results on function’s internal resonance

7.4 How to enhance risk assessment with resonance analysis

Risk analysis could be more precise if it could benefit of resonance analysis. To do so, the original dataset has been edited and two columns has been added (backvar for resonance from background functions and intvar for resonance inside the target function). On that database another random forest training algorithm has been tested, with the same parameters that has been previously used (3000 trees with 3 nodes, on 80 percent of data leaving the remaining 20 percent for validation tests). New mean decrease accuracy and mean decrease Gini parameters has been calculated, as shown in figure 11.

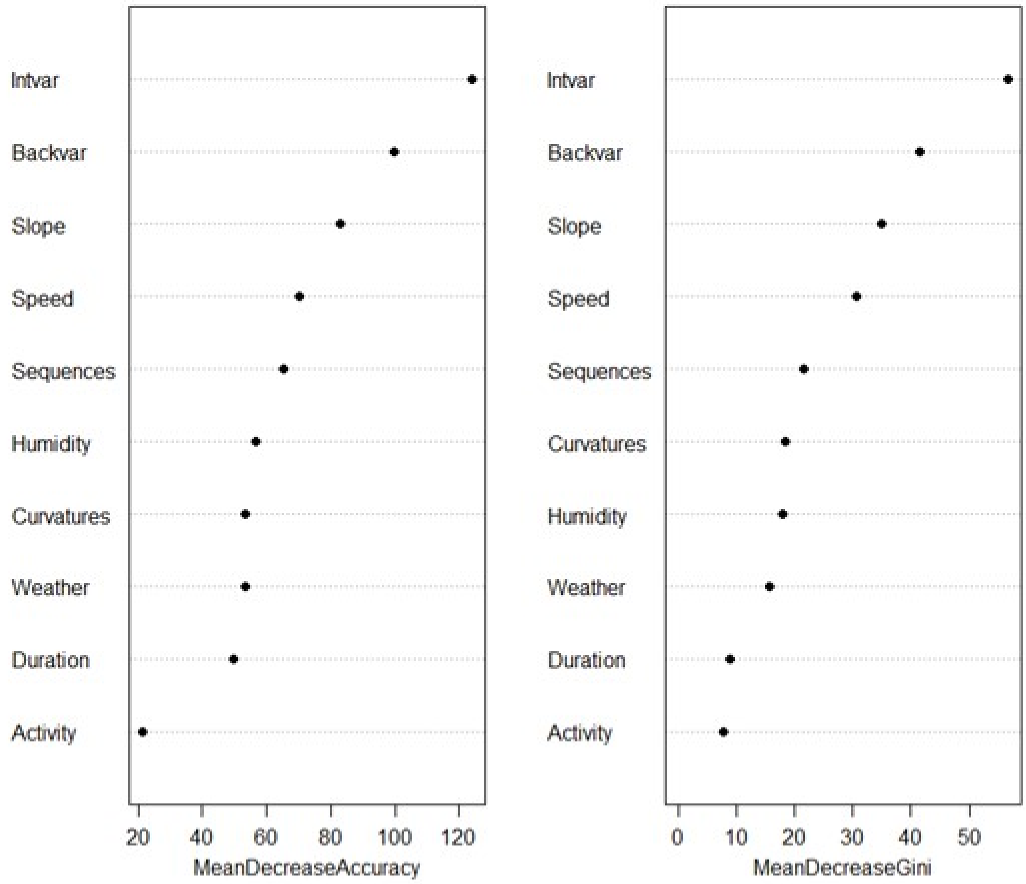


Figure 46: Mean Decrease Accuracy and Mean Decrease Gini for the database including internal resonance (intvar) and background resonance (backvar)

It is clear that internal resonance and external resonance provide additional information which is vital for risk assessment, and figure 10 confirms it. Another check on Euclidean distances and 3D distances on the dataset has also been done, in order to understand how it changed with the inclusion of two new columns.

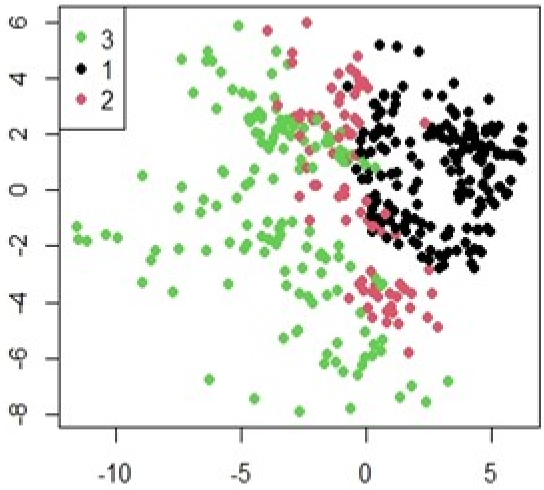


Figure 47: Euclidean distances including resonance

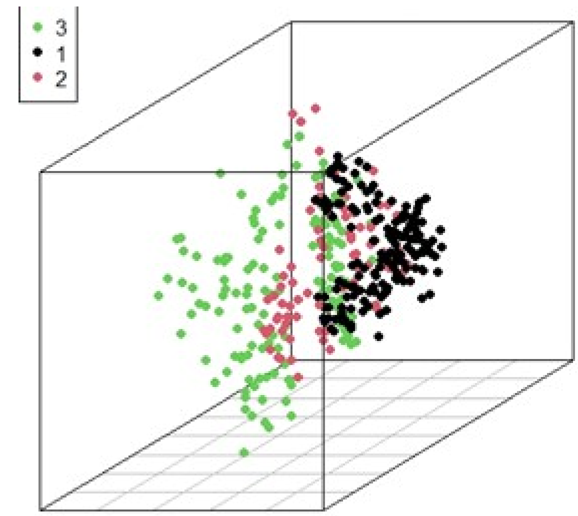


Figure 48: 3D distances including resonance

Figures 12 and 13 show that the inclusion of two new columns representing internal resonance and background resonance might lead at first sight to an increase of entropy. It has to be kept in mind that such columns are based on the dataset itself, so they can only give extra stability to the risk assessment classification. From random forest analysis, an average OBB error of 4.5 percent has been obtained and results are shown in the following table.

Prediction	Label 1 (low risk)	Label 2 (medium risk)	Label 3 (high risk)
Predicted as "Label 1"	51	1	0
Predicted as "Label 2"	0	11	0
Predicted as "Label 3"	0	1	36

Table 21: risk classification based on data and resonance analysis

Classification showed an accuracy of 98 percent. Extra randomization or algorithm tuning can produce slightly different results, but no more than 1 percent in reduced accuracy. 1 percent of predictions labelled a medium risk entry as low risk, remaining 1 percent of predictions labelled another medium risk entry as high risk. Given the small amount of "Label 2" values, the dataset has been utterly enhanced with the addition of 100 new entries for medium risk. A new random forest algorithm has been trained on this dataset: OBB was nearly 3 percent (Label 1: 0,005; Label 2: 0,04; Label 3: 0,06). After training with 480 entries (80 percent of the dataset) the algorithm has been tested with remaining 20 percent of values (120 entries), obtaining an even greater reliability (close to 99,2 percent) as shown in table 5.

Prediction	Label 1 (low risk)	Label 2 (medium risk)	Label 3 (high risk)
Predicted as "Label 1"	44	0	0
Predicted as "Label 2"	0	31	1
Predicted as "Label 3"	0	0	44

Table 22: risk classification for based on data and resonance analysis (600 rows)

The only mistaken prediction happened for a high-risk entry (Level 3) which has been labelled as medium risk. The algorithm has improved thanks to the better-defined Label 2 entries, avoiding some mispredictions that has been made before.

7.5 Conclusions

Functional resonance provides extra information about system's safety since it can show anomalies, hidden hazards and describe with more details what can be assessed as safe or unsafe. The implementation of a machine learning algorithm on pure risk assessment showed good results, but still with an important degree of uncertainty (correct predictions = 96 percent; optimistic predictions = 2 percent; pessimistic predictions = 2 percent). Additional machine learning algorithms on internal resonance and background resonance has also been tried, producing very promising results which in some cases could lead to a good prediction with no mistakes or could even be evaluated by hard-coding the classification rules. Finally, an implementation of functional resonance inside the original dataset used for risk classification performed better than the original risk assessment learning algorithm, with extra accuracy and less misclassification (correct predictions = 98 percent; optimistic predictions = 1 percent; pessimistic predictions = 1 percent). If the dataset is homogeneous even better predictions can be achieved, as shown for the last dataset made with additional rows (correct predictions = 99,2 percent; optimistic predictions = 0,8 percent; pessimistic predictions = 0 percent). Further enhancements can involve an even bigger dataset with more additional entries, and an application on larger scale by analysing various sources of resonance inside a complex system.

References

[1] E. Hollnagel, *FRAM: functional resonance analysis method.*

[2] L. Breiman, "Random forests," *Machine Learning*, vol. 45, no. 1, pp. 5–32, 2001. cited By 61132.

7 Analysis of expected outcomes and practical solutions

7.1 Principles for performance-bases safety management

Finding every key instantiation in agricultural activities allows to develop a series of possible strategies that can be put into practice to prevent accidents in many different ways. It is worth mentioning that since FRAM is based on resonance, negative outcomes must be managed by identifying actions that can be put into place in every function that is involved in the production of that resonance since there is not only one source and it is rather produced by tight couplings inside the whole system.
Possible strategies include, for instance:

- Prevent safety-critical measures from being deactivated, bypassed or removed. In case such actions are required, alternatives must be found to allow prevention or protection devices to continue to be effective;
- Resonance can be diluted along the downstream functions that still have to start, so it is not required to immediately stop working or solve the issues before passing the input to the next function;
- Effects from background functions should be carefully analysed because, sometimes, negative impacts from them are inevitable and cannot be avoided (i.e. market demand, market values, financial requirements, natural disasters, adverse weather).

These strategies can be included in management systems as a way to deal with unexpected events in a resilient way. Activities could be classified and assessment can be made regarding the most resilient solution that can be put into place.

7.2 Tools for a competitive safety strategy in agricultural workplaces

Competitive safety strategy relies on the possibility to develop a fairly good safety management system designed to provide the safest possible working environment while maximising production. Loss prevention can be seen, in fact, also as production loss prevention by reducing or eliminating downtime scenarios and by keeping all the workers fit to perform their job without injuries or long-term effects of poor working conditions on their working performances.

First of all, based on the AECAT instantiation, cost analysis can be assessed for every scenario. Accident scenarios also provide quantification of severity, so that comparisons can be made. Another step would involve a forecast of how many days/activity cycles will have to be performed under certain conditions, addressing them accordingly to the efficiency, compliance, ALARP, thoroughness or any other previously identified working mode. Great advantage can be generated by planning new work procedures which can allow efficiency scenarios to be converted into compliance scenarios.
Given the opportunity of promoting an activity to a much safer working mode (i.e. effectiveness to compliance or compliance to ALARP, etc) additional improvements can be found in moments of the activity which do not carry much concern about safety. This would provide higher safety levels without great economic efforts.

7.3 Functions and strategies to dampen variability

Despite safety management tools can be a reliable source for managing variability and avoid tight couplings among functions in activities, internal output variability still remains a threat. In order to utterly improve safety at work in agriculture, a series of actions can be put into place to dampen internal output variability or, at least, reduce those tight couplings that might result in accidents. The actions can be listed as follows:

- **Workers' rotations in critical tasks**, which allows to ensure that decisions that need to be taken on the spot are made by workers that are not too tired or stressed. During agricultural activities the workers, i.e. tractor drivers, have short time to decide what to do in critical situations and even when it is not a matter of time they still have to struggle to find the right thing to do among a lot of possibilities. This clearly shows why it is not possible to speak of "human error" anymore, because the same mindset can lead to responses that avoid accidents or that provoke accidents. At the same time dangerous approaches to tasks can also provoke no accident at all, but yet take part in generating internal output variability and, as final consequence, system resonance. Good ergonomics on machinery such as tractors or self-propelled machines are also required in order to avoid too many rotations;

- **Up-skill specialised personnel**, since better trained and experienced workers can both improve safety and production. Many times a well-organised training and safety information program at work also allows specialised workers to detect unexpected or abnormal output variability or conditions in their tasks. This kind of approach builds safety culture in the working environment and the possibility to rely on workers that know what to do in case of emergency will eventually result in influencing tasks as the presence of an utter layer of safety redundancy into place, for both risk prevention and protection;

- **Forced checks of variables to reduce tight couplings**. If certain upstream to downstream coupling are known for being hazardous, the function must stop until the abnormal output condition comes back to normal. Despite this kind of action doesn't really fit with an efficiency working mode, it can be considered as the ultimate way to prevent accidents when no other solutions are available and something must be done to avoid severe consequences to workers or, for preventing availability losses, even to machinery and equipment. This is why a forced check to solve a set of issues that might lead to accidents can be considered a valid effect even when time is crucial. Additional actions might be required as well in order to eliminate resonance in the system, so more functions might be needed to effectively carry them out;

- **Creating space among functions or tasks in a function**, by requiring a certain amount of time to be spent in another task while waiting for better conditions to carry out the function. It might even include pauses or any other activity which is meant to eliminate or reduce the possibility of making bad decision under pressure, and despite time can be critical in certain instantiations it is not a matter of wasting it but rather investing it to save time later since anomalies will not rise anymore and the probability of accidental stops or component failures in the activity will certainly be lower;

- **Driver assistance tools**, which can be meant to better perform a task but also keep track of dangers as they arise. Such tools include obstacle avoidance systems or any other system which, for example, tracks weather conditions and provides alerts if adverse effects on the task are detected. Roll-over prevention devices can also be named regarding tractors, based on curvatures, terrain slopes, speed and providing counter-measures even without driver's intervention. These tools can fall under SAE (Society of Automotive Engineers) J3016 standard ("Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles") on automation level 1 and 2, meaning that partial automation is included as, for instance, emergency braking or adaptive steering and cruise control. This example, even if it is taken from automotive industry, shows how simple it could be to improve tractors' safety by exploiting technological innovations regarding autonomous vehicles;

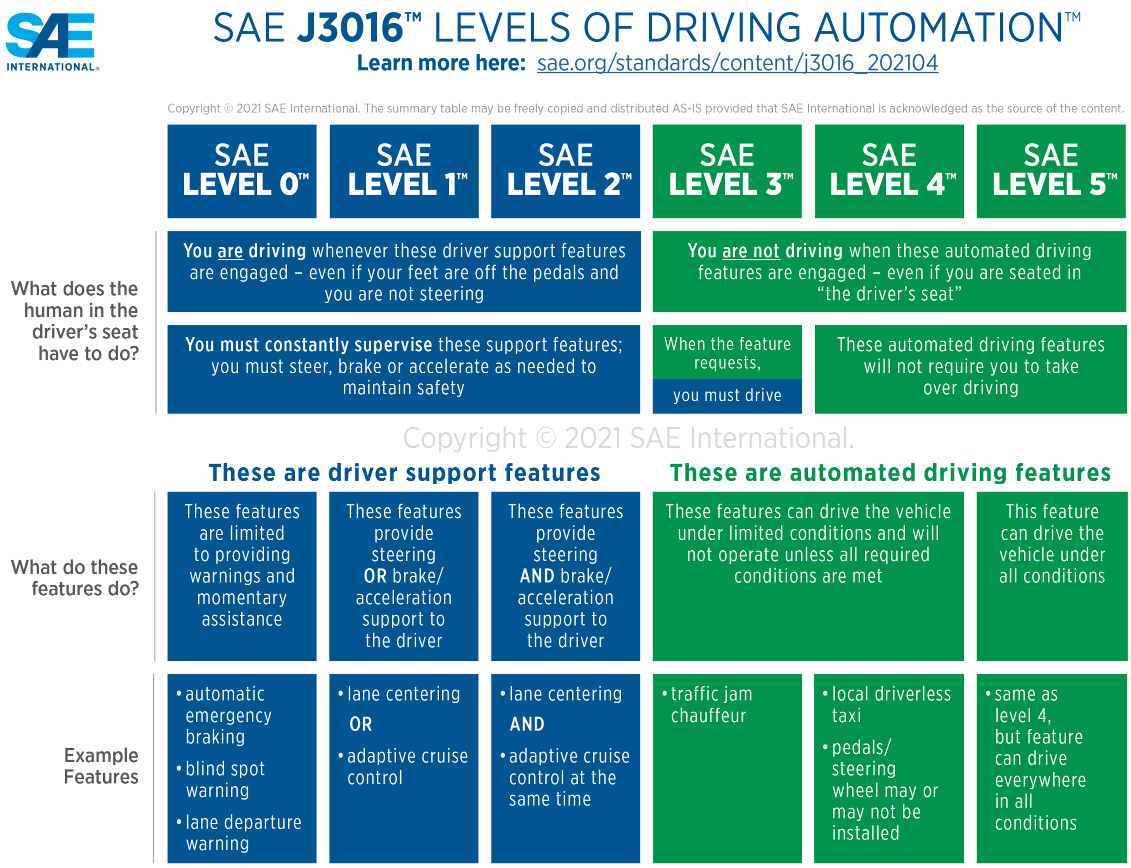


Figure 49: SAE levels of driving automation

- **GIS based controls**, these tools can detect the safest pathways for a tractor or, in case, generate warnings if tractors approaches an area with high slope percentages or harsh soil conditions. This can be performed onboard by sensors with the aid of GPS information or, instead, be elaborated on a separated server and provided to the tractor: in that case a reliable source of information, such as geospatial referencing systems, must be present and available without downtimes during the whole task with no interruptions;

- **Accident prevention functions**, that as already said can work as additional functions of the activity as one of the tasks it is made of, with the aim of recovering missing information, parameters, handling any increase of output variability and provide dampening effects by turning keeping the activity on safe instantiations. Such functions can include part of the actions already mentioned before, but they must be put in series with workflow rather than working in parallel with other tasks.

More actions can be utterly identified, but the seven listed above can work as pillars for additional tools.

7.4 Discussion

New methodologies that combine safety and production have been largely explored before already, but they have mainly been related to quality, reliability and savings on production losses. The heart of the approach showed in this thesis is making safety management mandatory to increase productivity, taking various instantiations that describe an activity as a way to increase the knowledge on how work is carried out in several different (and critical) scenarios rather than just on paper (work as done vs. work as imagined).

The FRAM-based approach discussed in this research allowed to obtain a semiquantitative methodology for risk assessments in agriculture that can be integrated in quality management systems and safety management systems. Since the original method was qualitative-only and its instantiations only represented particular moments of an activity (i.e. accident events), the dynamics of performance variability could have only been shown by listing upstream to downstream couplings and eventually provide information regarding their resonance and effects. A detailed analysis of particular scenarios like work carried out in an effective way, or only in ways recommended or permitted by laws and regulations, or again by following ALARP principles or performing it in a thorough way highlighted a series of parameters, functions, external variables and other aspects which influenced the activity and were responsible of any switch among the identified working modes. This is why those four states of work as done can be integrated with extra working modes in order to perfectly describe how every adjustments in performing the activity can generate significant differences in its outcomes. The most critical aspects in practical applications of the farm relied in the aforementioned limit in qualitative analysis only and in the need of continuously changing the way in which the activity could have been represented in order to follow the workflow in an exact way. The first critical aspect has been overcome and now semiquantitative outcomes can be produced, but the second critical aspect still remained an issue for safety analysis purposes: the type of activities that are present in agriculture, although, proved to be very linear and thus simplifications have been possible so that the workflow in foreground functions doesn't change at all. This is a clear advantage and a comparison with many other working sectors would show that the same methodology cannot be applied in every context. Agriculture and forestry can be considered tractable contexts for a simplified method of task analysis and FRAM instantiation analysis, so will do all the working environments that show linear activities with few or no changes in how they can be carried out but show instead many possible sources of output variability coming from background functions. Similar cases could be found in the fishing sector, or in any other working environment which involve few ways in which an activity can be executed and external variables that might affect it.

Since activities can be represented by main tasks that are always linked in the same way in all the analysed instantiations, every change in their behaviour can be tracked from start to finish, enabling a series of control procedures that can be run by checking sensors and other data through specific algorithms. The possibility to constantly track any change in significant variables which result in output variability allows to perform live control on the activity and determine which instantiation is the most appropriate minute after minute. The right instantiation will be chosen among those that have been predetermined by analysing the context, this is why machine learning perfectly fits the role of working mode classifier. As it has been shown in chapter 6, such algorithms like Random Forests not only help with classifying instantiations but also identify which features (variables) are the most responsible for label changes (switch among working mode). This is the advantage that suggested, in the beginning, to exploit such algorithms for safety-related classifications.

The presence of tools that can detect internal variability provides the possibility to include specific actions meant to produce dampening effects on variability, as previously shown in this chapter. These kind of solutions increase the possibility to identify dangerous conditions which may arise from abnormal values in certain aspects of a function that are also

non-critical at the same time and could not be detected by any safety device or specific procedure.
Having a system which can directly manage its internal variability can improve the chance of being resilient against external variability. External sources of variability can be identified as weather, environmental conditions, soil conditions, natural disasters but also other types of pressure that an activity can suffer: it might be related to short time availability as a small amount of time for too many tasks to complete or a deadline which might be challenging to respect, or market demands and any other financial reason that imply that an activity cannot be further postponed. All those possible sources of external variability influence an activity's tasks in a predictable way and, in some cases, in a well detectable way: this is very important since those variables are often responsible of switching from one way to carry out the activity to another.

7.5 Conclusions

Conclusions can be drawn regarding the possible expected and practical outcomes derived from the application of the methodologies presented in this research. The most important aspects are listed below:

- Dynamic assessments can now be generated, even if static assessments are still needed for specific conditions like accident analysis. This can be made operational by safety management tools but can also generate a new way of safety analysis for agricultural machinery which must take into account external conditions as paramount to any assessment that can be made on the usage of the machines as it can be imagined;

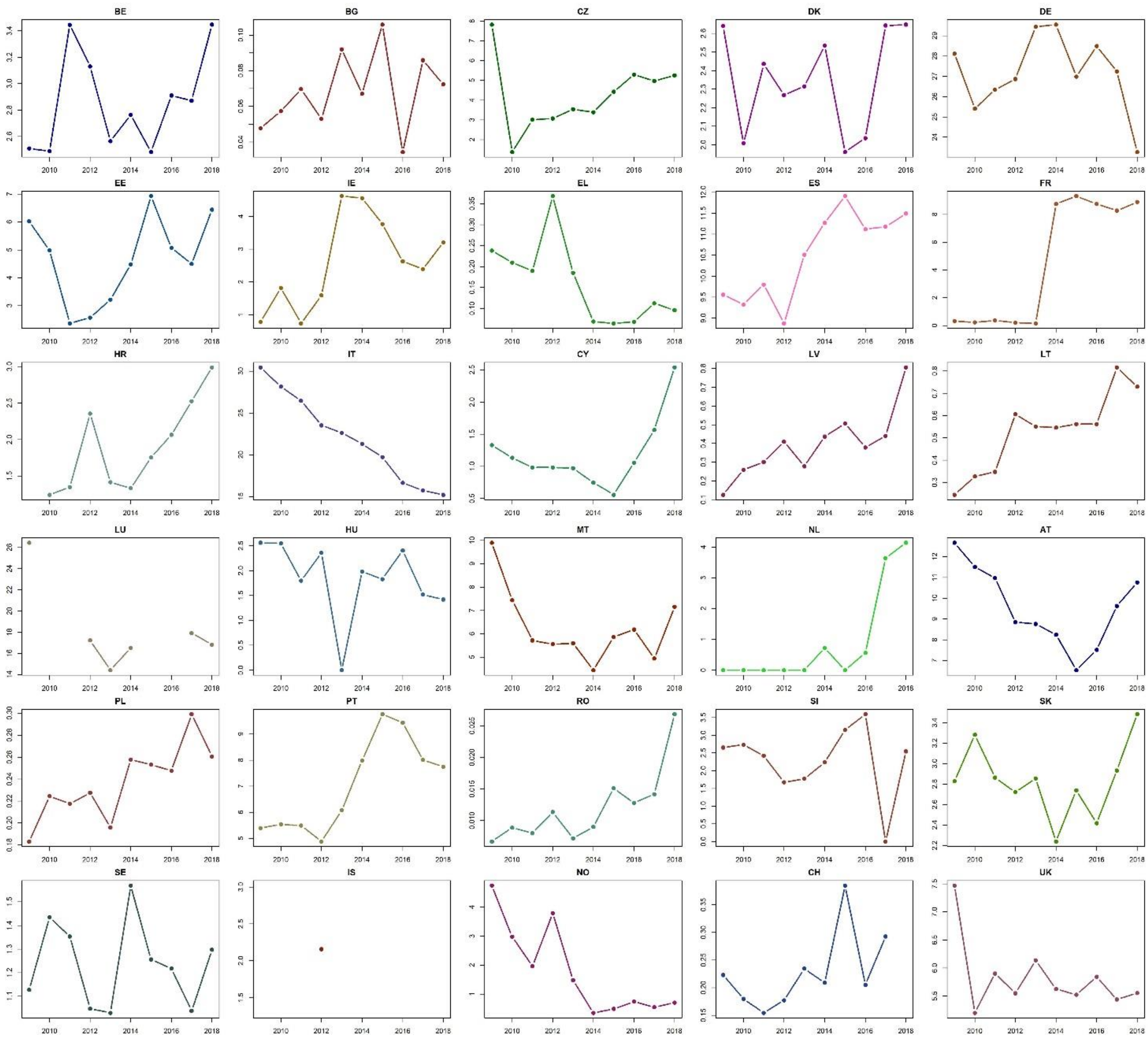
- There is now the possibility to execute certain activities with a fairly good level of safety even if compliance has not been satisfied. This is the key advantage to prove that safety can increase productivity and will not show it down at all, and safety analysis can serve as preliminary management tool capable to identify which tasks are the most critical for getting the right outcome from an activity. It can be seen as an enhanced reliability and availability analysis that takes into account farming businesses' necessities as well;

- The creation of a Competitive Safety Strategy by performance-based analysis methodologies for decision makers can be a valuable resource for policy makers too, since regulations might take in consideration to allow exceptions to minimum requirements if alternative and more feasible ways are available.

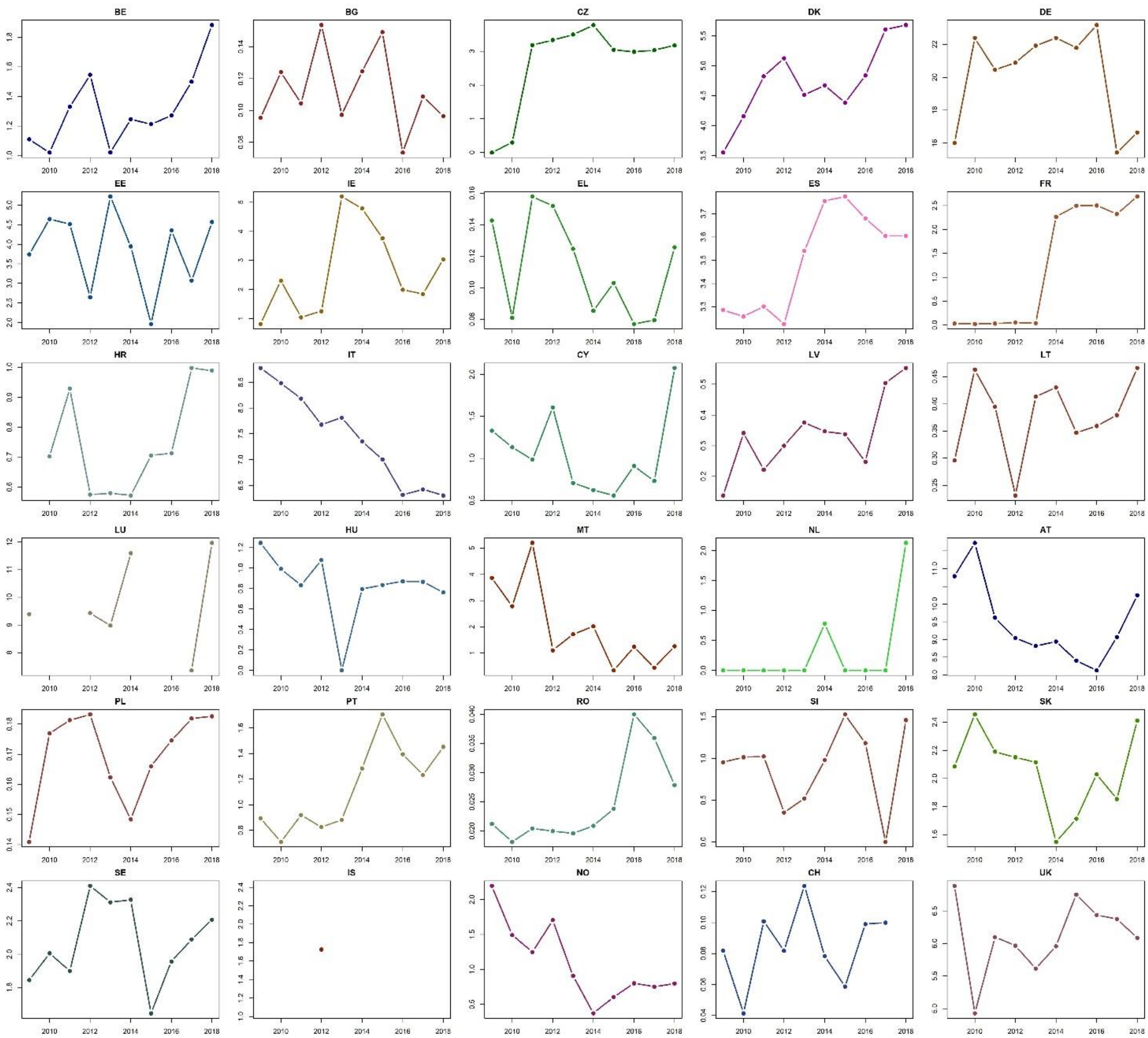
Improvements might be done in future on specific methodologies covered by this research such as management tools or internal variability detection devices, while additional ideas can be elaborated to refine the strategies for dealing with the most important instantiations of an agricultural activity in order to be able to generate pure quantitative assessments as well.

APPENDIX A – National data trends for accidents at work in agriculture – Severe injuries (non-fatal)

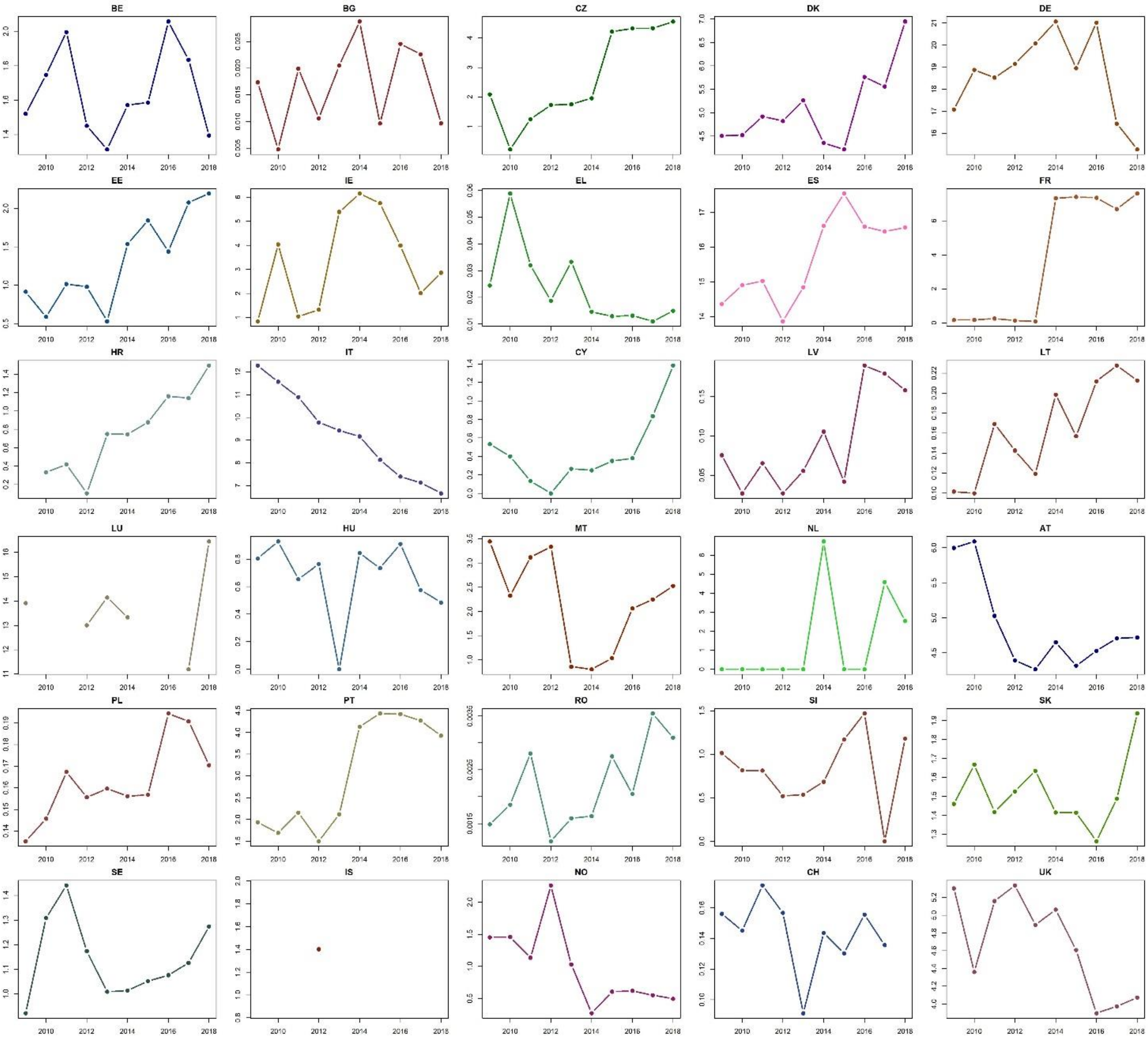
Wounds and superficial injuries



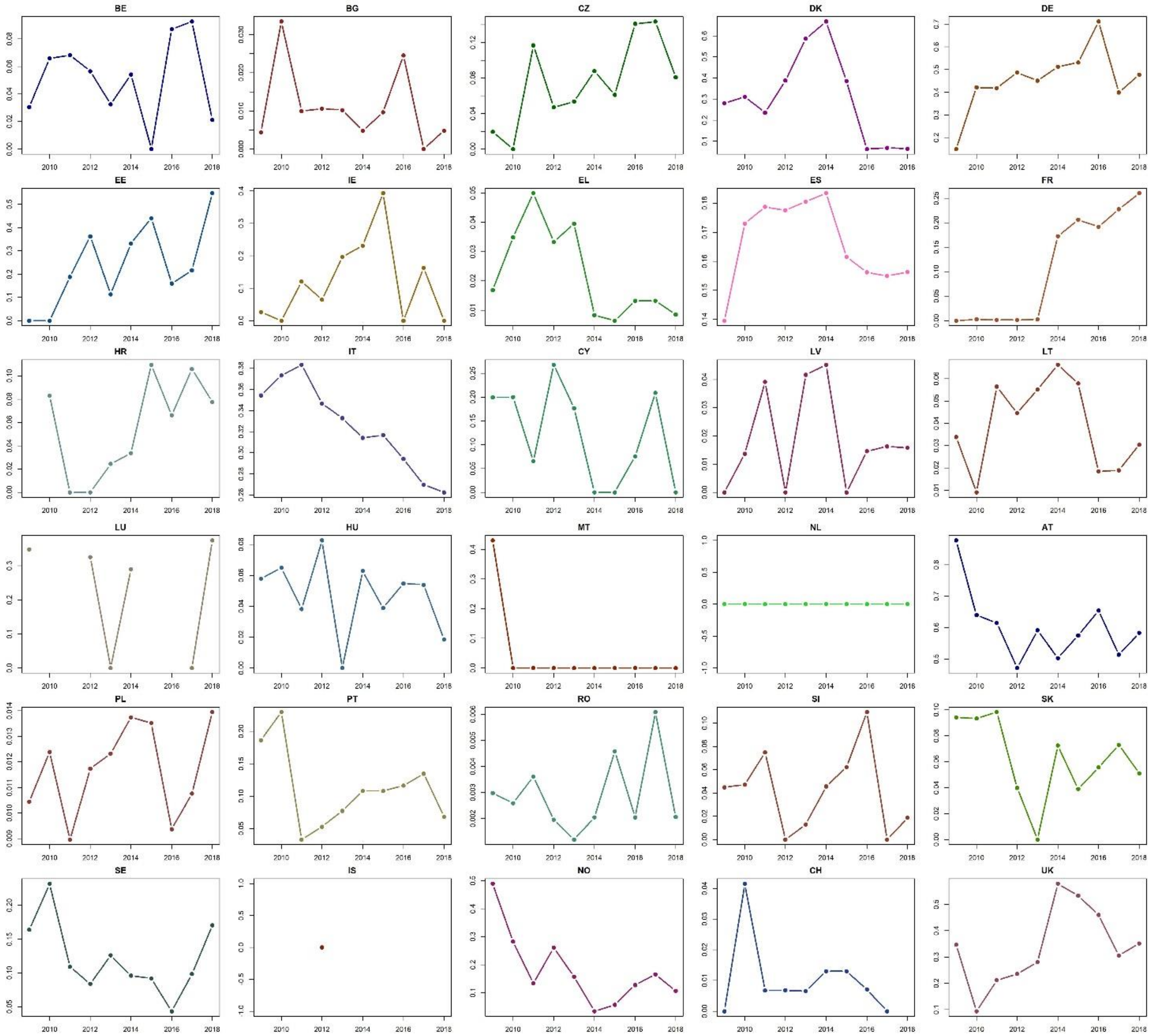
Bone fractures



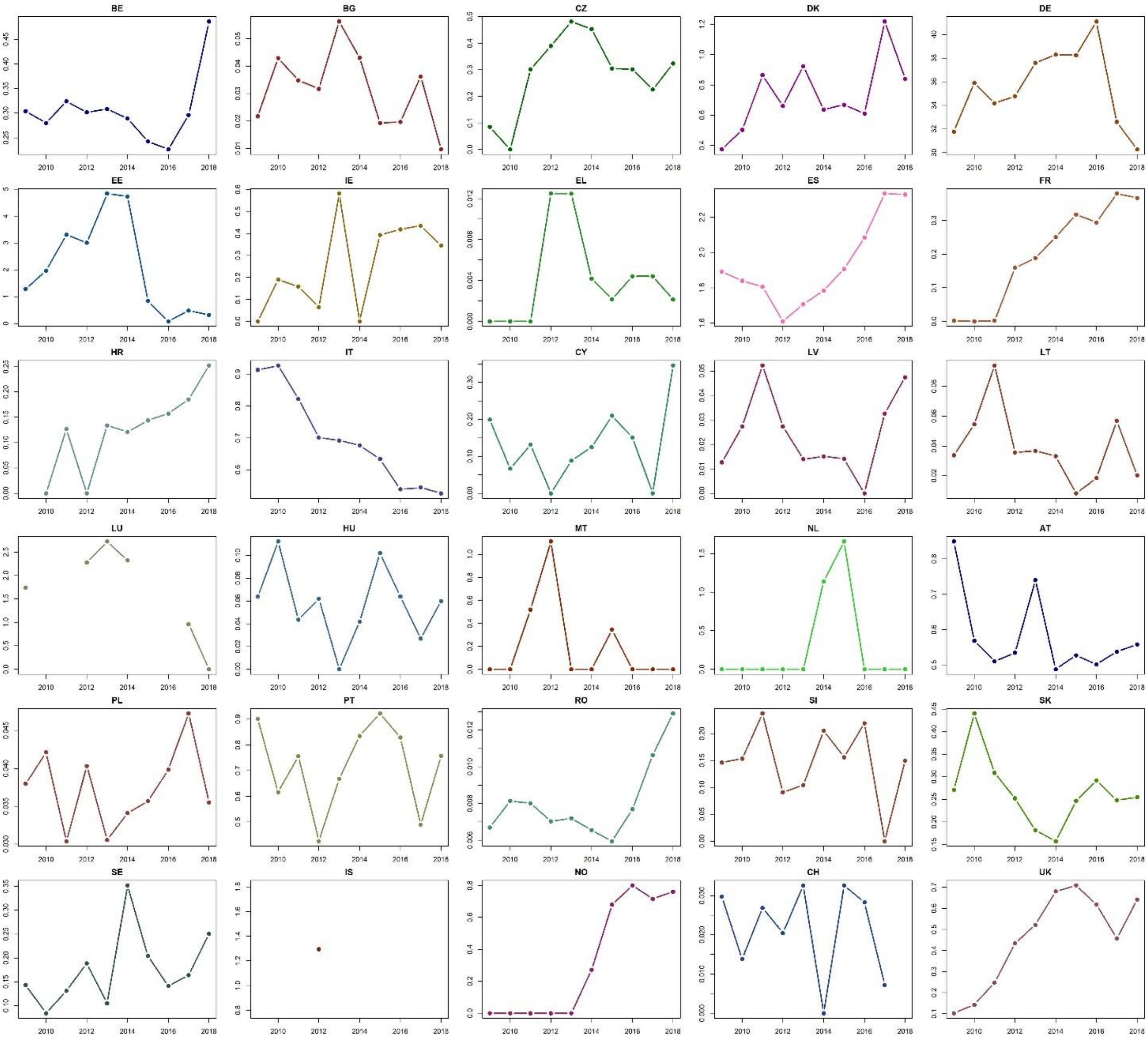
Dislocations, sprains and strains



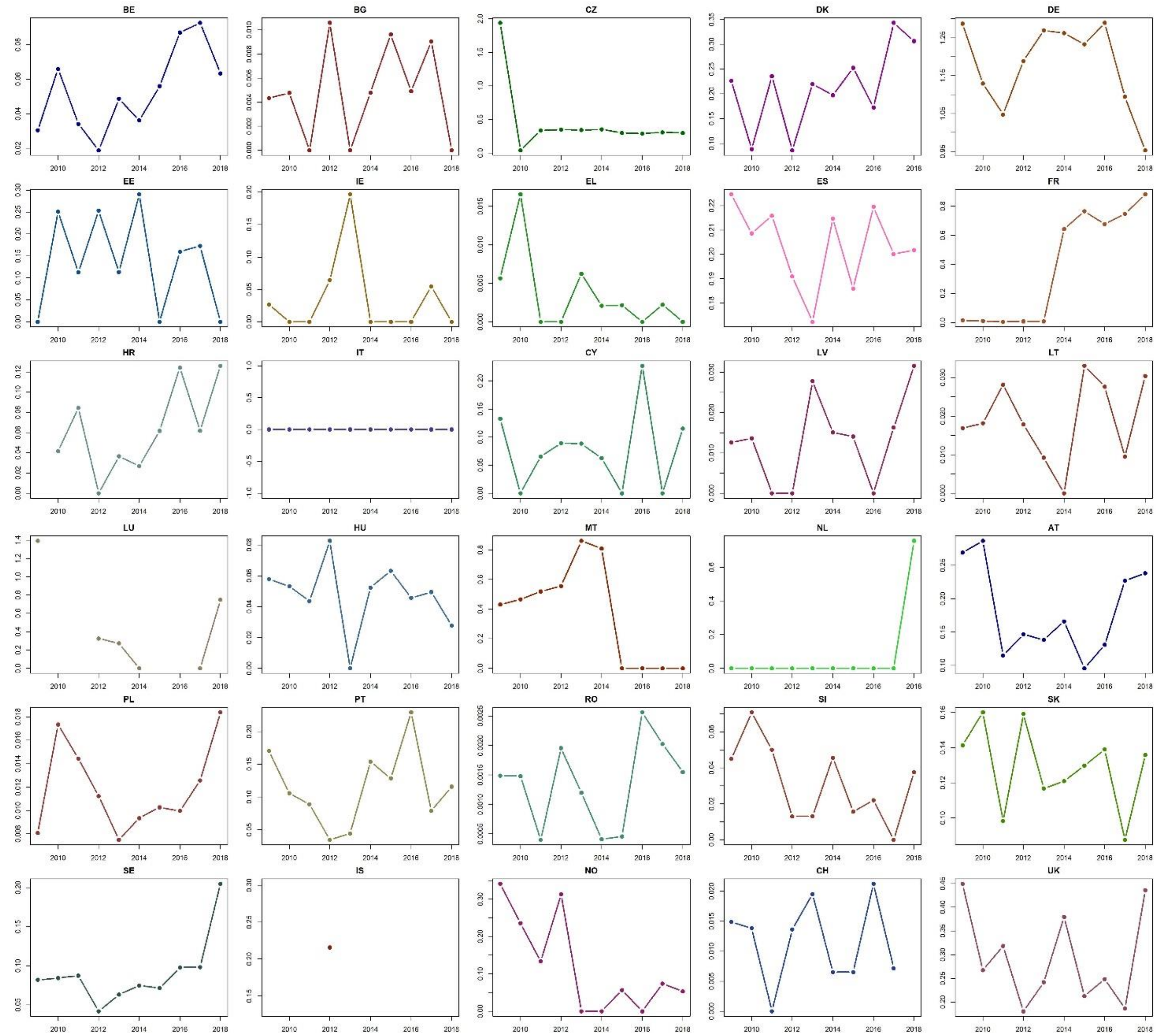
Traumatic amputations (Loss of body parts)



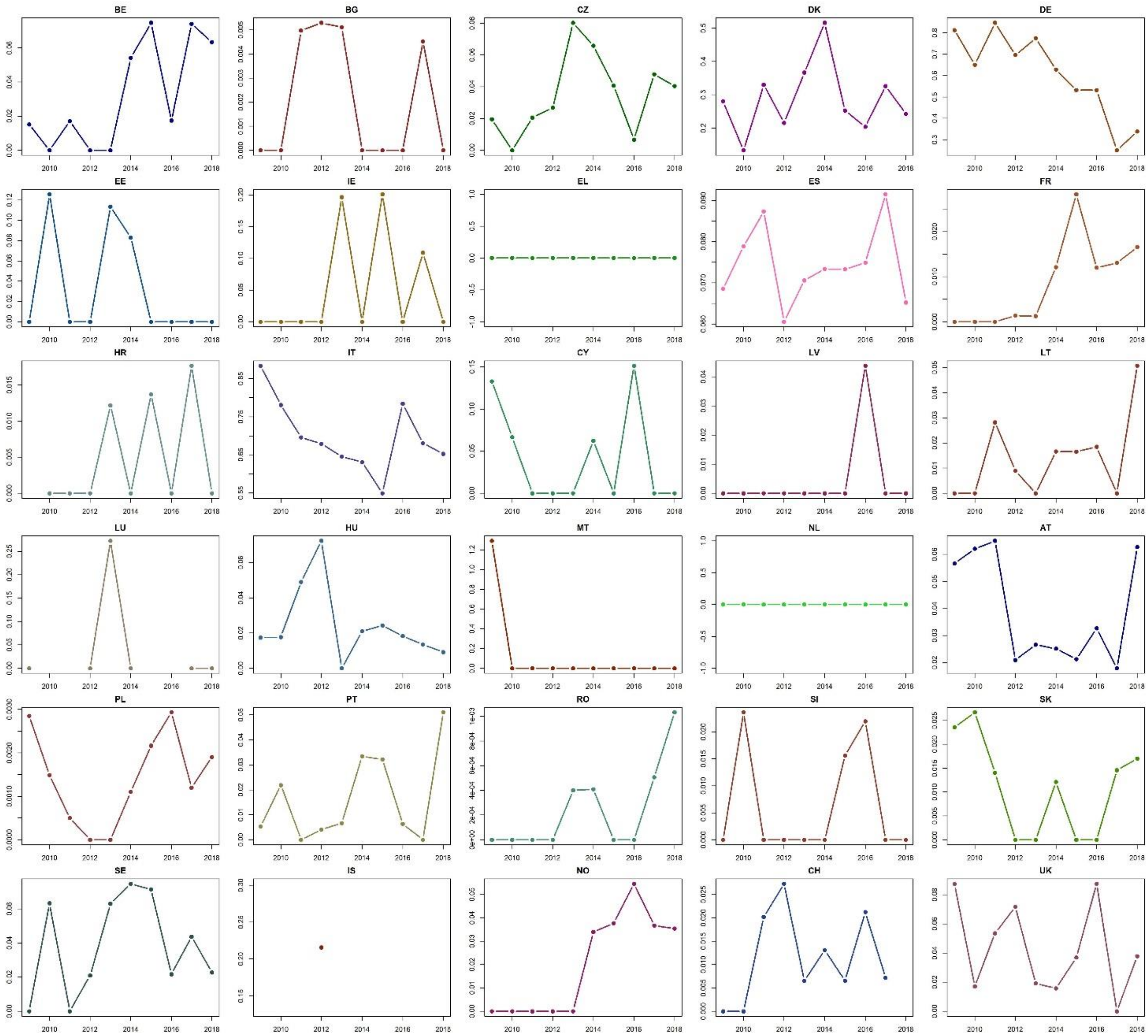
Concussion and internal injuries



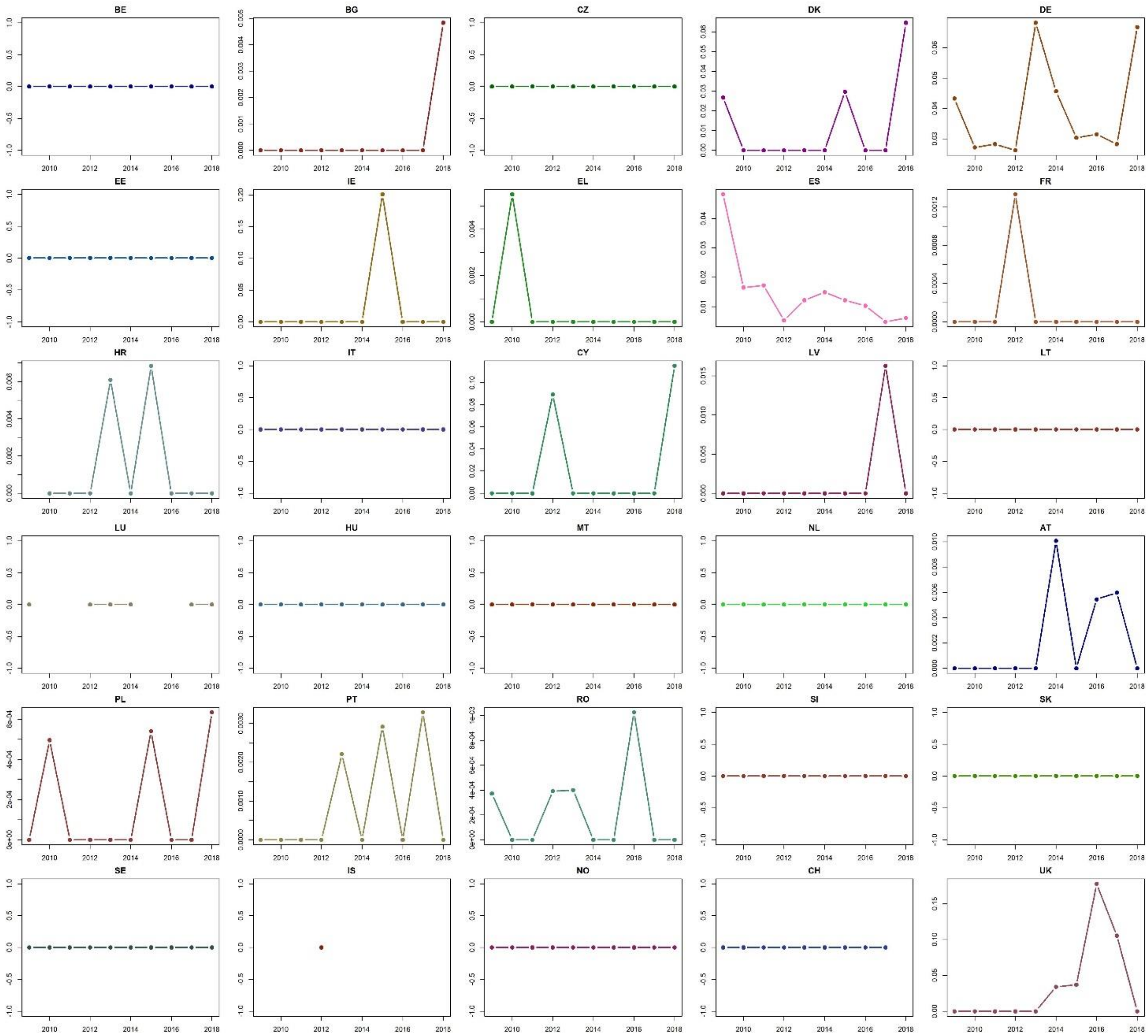
Bruns, scolds and frostbites



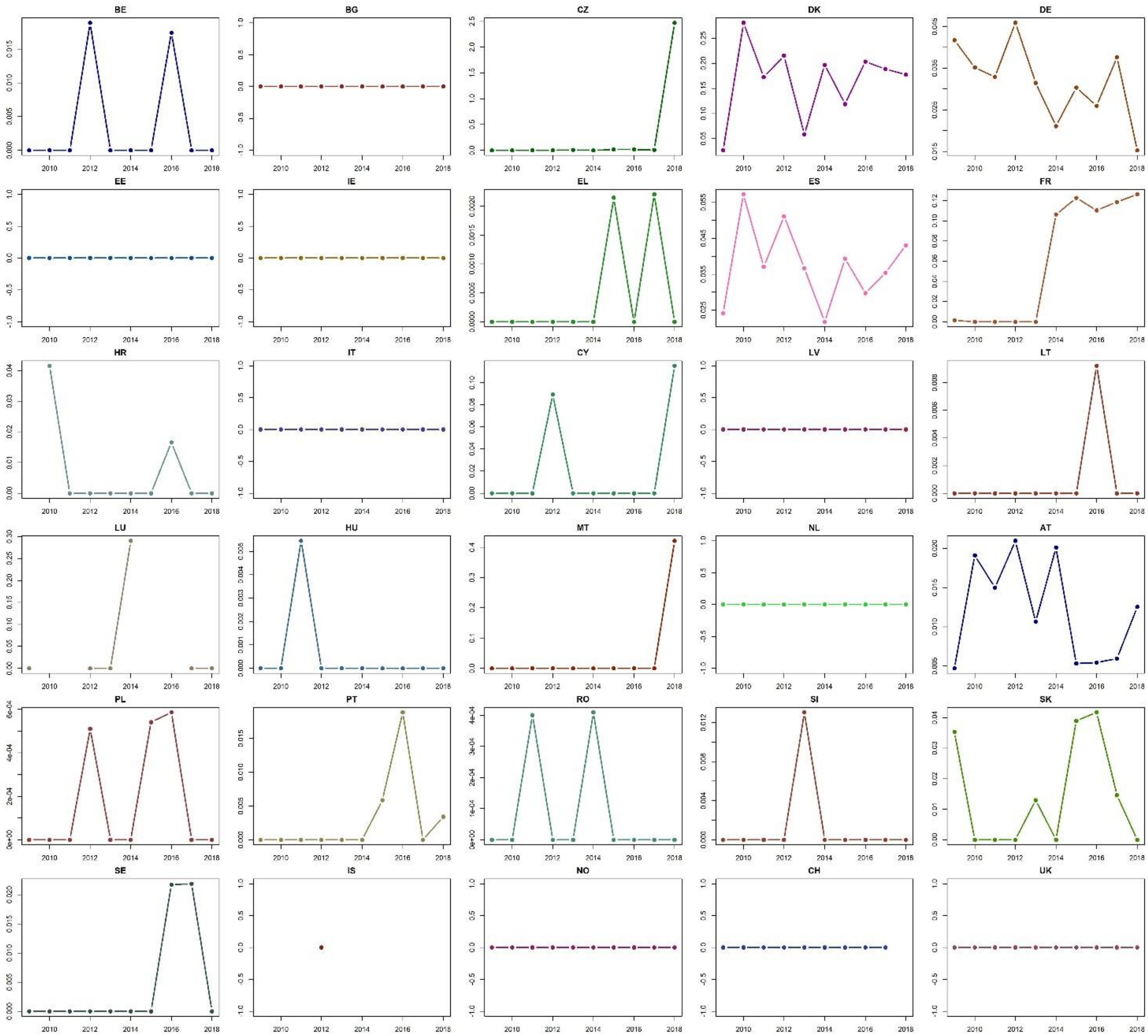
Poisonings and infections



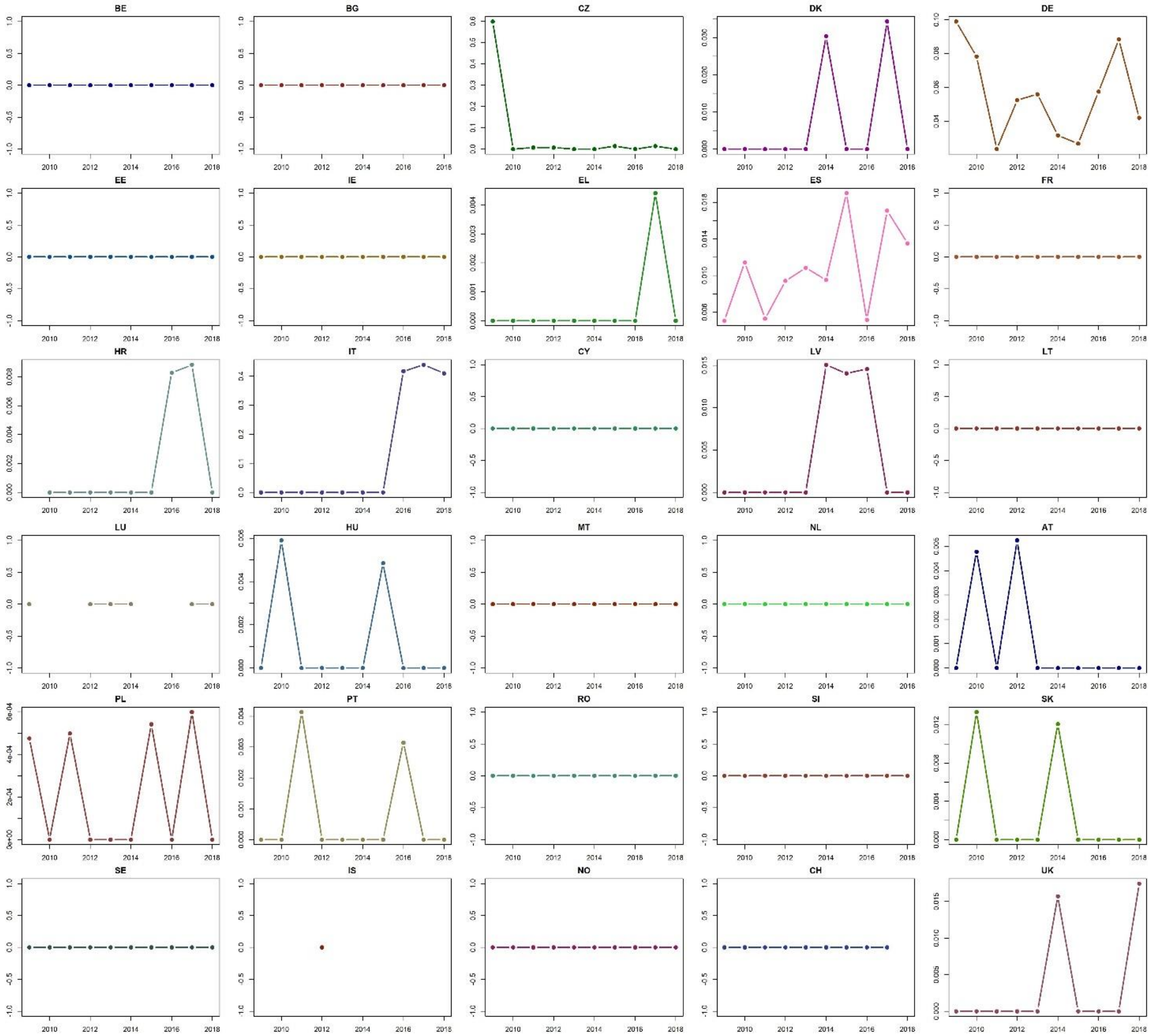
Drowning and asphyxiation



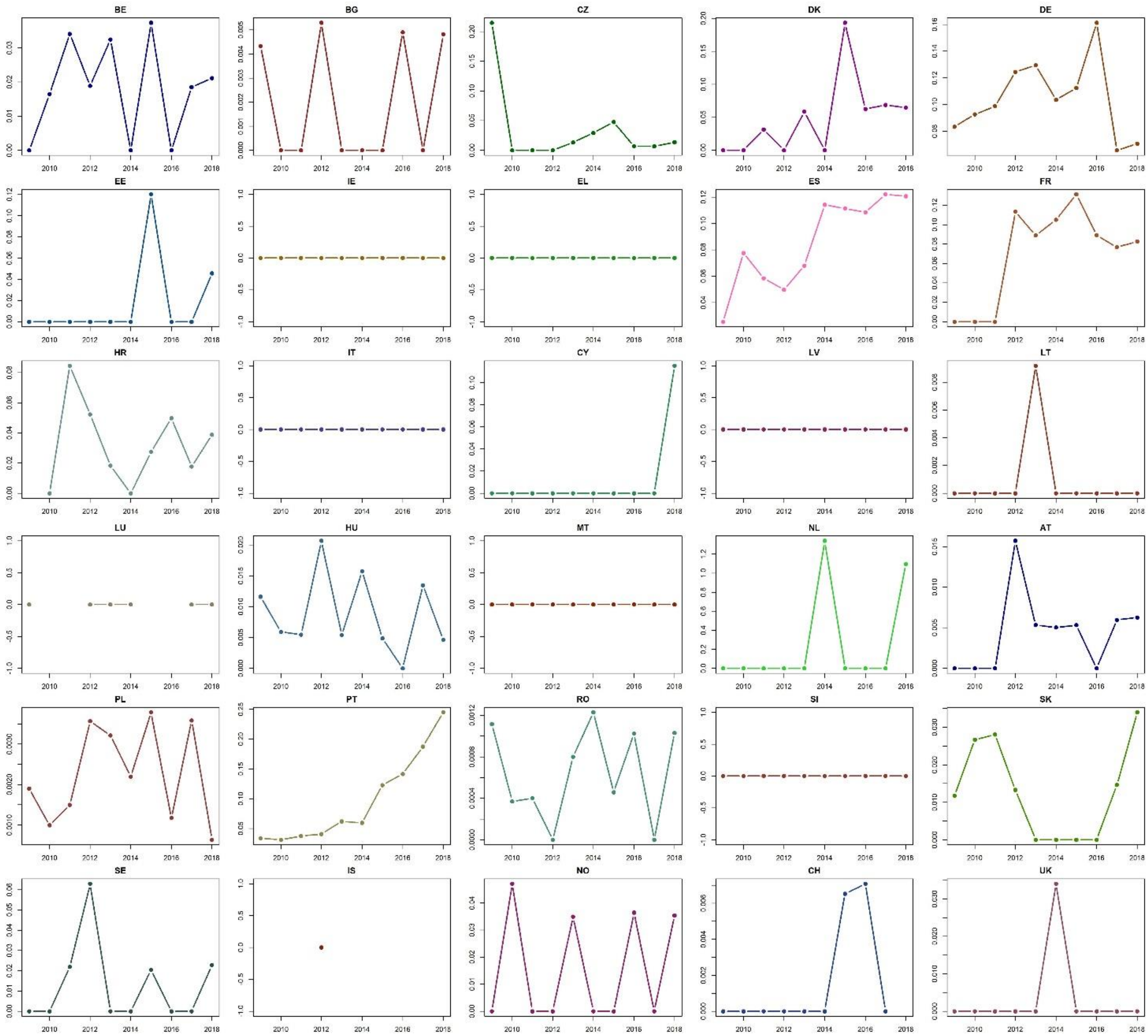
Effects of sound, vibration, and pressure



Effects of temperature extremes, light and radiation



Shock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Multiple injuries