Data-Driven, Information-Enabled Regulatory Delivery

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Foreword

This report looks at how data analysis techniques and information management tools can help make regulatory inspections more efficient through better risk analysis, targeting and co-ordination. It is based mainly on work conducted by the OECD in Italy (funded by EC DG REFORM) to pilot the use of machine learning techniques and data-driven analysis for risk assessment and to improve information systems integration. The pilots, undertaken in the regions of Campania, Lombardy and Trentino,, cover several regulatory domains – food safety, occupational safety, and environment. They show how better use and management of data can improve inspection systems even within a relatively short timeframe. The approach is based on improving the identification and rating of risk factors, so as to focus regulatory efforts on those businesses or establishments with the highest risks.

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Abbreviations and acronyms

DDPS	Data Driven Public Sector
ESI	European Structural and Investment
FBOs	Food Businesses Operators
GISA	Cooperation and Management of Official Controls
ML	Machine Learning
Mo.Ri.Ca.	Site Risk Monitoring System (Italian acronym)
OSH	Occupational Safety and Health
RAC	Rating Audit Control
RUCP	Single Register of Provincial Controls on Businesses
TD	Trentino Digitale

Executive summary

Risk-based regulatory delivery can be made more efficient through data management tools and information technology

This report draws upon the results of three projects in different regions in Italy, covering distinct regulatory areas, to assess the increasingly important role played by data analytics in applying and enforcing rules.

The importance of risk-based approaches to regulatory inspections and enforcement is well known. However, regulators seeking to incorporate risk-based approaches still encounter roadblocks in terms of insufficient data generally and inadequate data management tools specifically. While using some risk analysis is more efficient than no risk analysis at all, data-related roadblocks have made it more difficult to identify risk factors. This problem has become more pronounced during the COVID-19 pandemic, where regulatory inspections and enforcement activities and related interventions had to be prioritised in order to balance safety concerns. However, recent developments have shown that data management can help improve inspection systems quite quickly, in an easier and cheaper way than in the past, because costs for equipment are lower, less specialist staff time is required, and computing power has increased. Developments in machine learning have also made the analysis of large volumes of data faster.

The role of machine learning is already showing promise in risk analysis and predictive modelling to improve regulatory inspections and enforcement

The use of digital tools is already well accepted in revenue fields such as tax and customs, where data is numerical and has been digitalised for longer. The initiatives covered in this report focus on regulatory sectors where data is not yet collected in a precise fashion and is often from different sources, including the subjective perception of the regulators. For machine learning to work well, data coherence is crucial to predict the level of risk, as well as attribute relative “weights” to various risks, as precisely as possible. Three projects in Italy focusing on three different regulatory areas – construction, occupational health and safety, and food safety -- used machine learning techniques to predict non-compliance. Results show that machine learning helped in identifying predictors of risk based on a business’ characteristics, including its previous record of non-compliance. In the case of the construction industry, which is traditionally a high-risk sector, the machine learning tool is programmed to identify sites with the greatest risk. This can help ensure limited resources are used most effectively. Machine learning systems are also helping regulators integrate operational and strategic functions while co-ordinating with multiple stakeholders in a given regulatory sector. This can help with risk prediction and, through data collection and machine learning techniques, with the monitoring of operators.

Data-centric tools can be used to create a single register for different inspectorates

In Trento, the Single Register of Provincial Controls on Businesses (RUCP) collects data from the enforcement activities of different inspectorates as well as data on objective business characteristics. Scorecards will be used to develop a risk profile for regulated establishments. The goal of the RUCP system is to help inspectorates better plan their control activities. With the Rating Audit Control (RAC) engine, the RUCP will be able to carry out risk analysis and rate operators according to risk. Moreover, the system allows sourcing of data from multitude of agencies, and thus can help prevent overlapping among inspection activities. Performance to date of the RUCP has highlighted the need for concise definitions and functions – currently developed using the Inception Deck methodology. Once scorecards of existing risk parameters are available, the system can then perform predictive modelling.

The report describes the system architecture that the RUCP would use to assess the risk level of a given operator. It explains how data is exported from different sources to the RAC engine after which it is cleaned, aggregated and put into a simple format for running in the algorithm, which will then produce the prediction and risk classification to be used by each inspectorate. Currently, this system is managed by the regional public IT company– *Trentino Digitale,* with support from other suppliers outside the company.

Areas for future development

The last part of the report outlines some of the current challenges and scope for future improvements in the performance of data-driven regulatory delivery. Easier and cheaper access to data and data processing, in addition to time-tested knowledge of inspectors, will allow regulatory delivery activities to be carried out in a more risk-based and targeted way, thereby reducing burdens. However, lessons from the current projects in the three Italian regions have also shed light on future issues that need to be addressed. At present, predicting the impact dimension of a given risk is difficult. Furthermore, artificial intelligence and machine learning assess the greatest risk of non-compliance, but do not always contribute to making the regulatory system better at identifying the "unknowns". The quality of data still remains a challenge, especially in regulatory areas traditionally non-revenue based. Currently, there is a need to build capacities in the design and development on digital systems and use of data; inspectorates without adequate training are not able to reap the maximum benefit from the system. Privacy and data protection concerns are also on the rise. The *OECD framework for digital talent and skills in the public sector*, as well as its data governance guidelines, provide support to countries in addressing several such issues.

1 Data driven approaches towards risk-based regulatory delivery

As the world goes more digital in the manner in which it functions, regulatory delivery also needs to be digitally enabled to better its effectiveness and efficiency. This chapter sets out the need for infusing data-driven systems towards conventional risk-based approaches. The first part explains risk, its various components and the inherent limitations in the current system. The second part introduces real-time applications of digital tools such as predictive Artificial Intelligence and Machine Learning in three OECD projects in progress in Italy.

Regulatory resources are inherently limited, compared to the scope of economic activities they are set to supervise. Economic growth and technology-driven transformations, combined with budget constraints, as well as significantly higher public expectations of regulatory protection from various risks (Blanc, 2015[1]), have made this mismatch increasingly important. Regulatory "delivery" (supervision, inspections, enforcement) is thus faced with major resources and effectiveness challenges – but it also can represent an important burden for economic actors (and, sometimes, create real barriers to growth) (Blanc, 2018[2]). Making it more efficient is thus a key priority, and risk-based approaches to targeting of inspections, as well as risk-proportional enforcement, have long been put forward as critical for such improvements (OECD, 2014[3]). Full effective implementation of risk-based inspections has at times been limited by a number of factors, including challenges in data availability and management, both to identify risk factors and assess risks of specific operators and establishments (OECD, 2018[4]). Technological improvements and increased use of data management tools in regulatory services present, however, considerable opportunities for improved implementation of risk-based regulatory delivery (OECD, 2015[5]). A Data Driven Public Sector (DDPS) achieved through data governance can help policy makers become more efficient and transparent. Alongside this, the use of data by public authorities, to plan, deliver and evaluate policy activities, should add to public value while at the same time, help foster institutional trust through privacy and transparency, in the minds of the public (OECD, 2019[6]). In the recent past, risk-based regulation of infrastructure projects using data analytics, have helped in identifying a data value chain and its common components for improving data analytics. These include effective institutional and data governance, data integrity and project planning (OECD, 2019[7]). This note presents several cases that illustrate the development of such initiatives and which could also provide inspiration for new ones.

Risk-based regulation (OECD, 2010[8]), including risk-based regulatory *delivery*, involves understanding the *specifics* of each risk (*risk analysis*) allows to better determine the most appropriate tools, assessing the *level* of risk (*risk assessment*) allows to select the most appropriate intensity of regulatory response (stringency of requirements, and delivery processes and resources). Studying *risk, its probability and scope,* allows to better formulate what it is that a given regulation is trying to address (reducing or managing a risk). Risk management is important to ensure the optimal functioning of the public authority and safeguarding of its integrity objectives and preventing harms (OECD, 2020[9]).[1] Understanding risk, its causes and characteristics, helps to better design the contents and mechanisms of the regulation and to target enforcement and implementation efforts more efficiently (on the areas, sectors, businesses etc. that pose the highest risk). It is defined as the *combination* of the *likelihood* and potential *magnitude and severity* of harm. This can also be expressed as the combination of the likelihood and degree of hazard.

Thus, risk combines a) probability, b) scope of the harm (number of people affected etc.) and (c) degree of harm (type of damage). *Harm* is any form of damage done to people (their life, health, property etc.), the environment (natural and human), or other public interests (e.g., tax fraud harms state revenue). Not all types of harm are of the same nature. Some harms are irreversible (e.g., death), whereas others (e.g., financial) can be corrected once identified. *Unpredictability* and *uncertainty* are distinct from risk and from estimations of probability of harm. They are *inherent limitations* in the process of risk assessment and thus likewise limitations of risk-based regulation, that should be acknowledged as such. Generally, risk criteria in most regulatory domains have typically been defined based on expert assessment (Blanc, 2012[10]) – with only revenue services having sufficient data to determine them based on quantitative analysis (Khwaja, Awasthi and Loeprick, 2011[11]). Collection and management of up-to-date and adequate information on supervised businesses was also an issue, even though good practices have been known for some time (Wille, 2013[12]).

Improvements in information technology (processing power and costs, Machine Learning methods, etc.), combined with the increasing number of regulatory services using digital information systems to record inspection results (thus providing crucial historical data), have combined to change the context, and create new opportunities to improve regulatory delivery (Mangalam, 2020[13]). From a regulatory perspective, data analytics is also proving to be increasingly cross-functional. It has both vertical and horizontal applications with the same data being used to pursue different regulatory objectives (OECD, 2019[7]). Data analytics planning to effectively assess risk objectives- including identification of data needs and sources, selection and understanding of data and the design and analysis of data itself have become far more streamlined. Building on previous work assessing existing practices and documenting improvements and reforms (OECD, 2020[14]), the OECD Secretariat has been involved in several initiatives to further research and support the use of information technology to make inspection systems more genuinely risk-based. Most of this work has taken place in Italy, at the regional level, as part of a project requested by the Public Service Department of the Italian Government, and funded by the European Commission – DG REFORM. This note presents the main findings and lessons from this work.

The project, called "Rating Audit Control" (RAC), aims at making regulatory inspections more targeted and risk-based, and works primarily at the regional level, where most technical and safety inspections are managed in Italy, with an important information technology and data analysis component. The activities support different regions and regulatory services in improving inspection planning by making better use of existing data and systems and, where possible, improving these systems in terms of risk integration. The project works in four regions – Campania, Lombardy, Trentino, and Friuli-Venezia-Giulia. However, bulk of the IT and data-related work has so far been conducted in the former three. This note presents the main activities conducted in these three regions- the application of Machine Learning techniques to improve the risk criteria used to target occupational safety inspections on Lombardy's construction sites (through the Site Risk Monitoring System, Mo.Ri.Ca.); the development of a risk-assessment "engine" for the Autonomous Province of Trento's *Single Register of Provincial Controls on Businesses* (RUCP); and work to improve the risk-assessment function of Campania's Integrated System for the Cooperation and Management of Official Controls (GISA), used for food safety inspections in the region.

- Autonomous Province of Trento: the project has been supporting the further development of the new inspections' management system, called *Single Register of Provincial Controls on Businesses* (RUCP), which has been under development for several years, but still covers only a limited number of inspection services. The focus has been on developing a "RAC Engine", relying on a set of algorithms (each specific to a given type of inspection) to allow the RUCP to produce a risk-based rating for each business or establishment, enabling inspectorates to select inspection targets based on their risk level.
- Lombardy: the assessment of existing data and information systems in Occupational Safety and Health (OSH) and food safety services revealed significant opportunities to apply Machine Learning techniques to improve risk prediction and thus inspections targeting. The initial focus was on OSH services, which use the Site Risk Monitoring System (Mo.Ri.Ca. in Italian) to conduct risk assessment for the planning of inspections of building sites. The work is gradually being expanded to food safety (assessment of risk in sites producing food of animal origin).
- Campania: the region has been a kind of "trailblazer" within Italy with the development of the Integrated System for the Cooperation and Management of Official Controls (GISA, in Italian), which has been in place for nearly 10 years and support co-ordination, risk-based planning and management of records for food safety inspections in the region. The project has worked to support the further development of risk criteria to improve the efficiency and effectiveness of targeting, and Machine Learning work on historical data is planned for the next phase.

Note

[1] See specifically Chapter 10, https://www.oecd-ilibrary.org/sites/ebbed075-en/index.html?itemId=/content/component/ebbed075-en.

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2 Applying machine learning techniques to inspections

This chapter details the manner in which IT tools have been used to manage occupational safety and health inspections in construction sites in Lombardy as well as food safety inspections in the Campania region. Brief mention is also made to other OECD projects involving predictive systems for assessing water quality and self-certification tools. These projects illustrate the moving away from the systematic use of data in revenue-based regulatory areas to other domains where data has been historically difficult to manage. The chapter adds the following key observations: i) Machine Learning can help predict indicators of risk; ii) Artificial Intelligence systems can help improve enforcement performance through quantitative analysis of inspections, and; iii) conventional assumptions of the best predictor of non-compliance are being challenged through Artificial Intelligence systems.

A key challenge in the implementation of risk-based approaches (and particularly for regulatory inspections and enforcement, for which risk is an essential instrument) is to adequately determine the factors that lead to increased risk and assess their relative importance. While revenue agencies had long started to systematically use data analysis techniques to identify risk indicators and their relative importance, this had until recently been difficult to replicate for non-revenue inspections. Data was either insufficiently digitalised, or too complex, or sometimes too narrow. Historical records were also insufficient, as new systems had been introduced too recently. In some cases, data systems with historical inspection records existed from earlier, but their scope was narrow and insufficient to identify risk indicators. Specific staff competences and capacity were also often missing. Despite these, an increasing understanding of risk-based regulation and of the importance of accurate risk-assessment (as opposed to reliance on “traditional” assessments of where priorities lay) have opened the way for a more systematic, data-driven approach. Despite remaining challenges in terms of assessing the “severity” dimension of risk, recent Machine Learning (ML) applications are very promising in terms of significantly improving the understanding of which characteristics of businesses and establishments are the best predictors of risk, and thus considerably improve the effectiveness of risk-based targeting.

While defining risk abstractly is relatively straightforward, developing robust methods to predict the level of risk of different businesses or establishments is far more difficult. Until recently, challenges in data availability and methods for analysis meant that defining risk criteria and their relative weights based on “data mining” or similar mathematical approaches was mostly reserved to tax and customs inspections, audit, infrastructure, health and social welfare programs (where the objects of regulation and control are inherently numerical, and computerisation was done earliest and in the most systematic way). In technical regulation, food safety, occupational safety, environmental protection etc., risk identification and weighting were done through a combination of scientific and technical findings, regulators’ experience and “trial-and-error”, but in a much less systematic and precise way.

The Mo.Ri.Ca. system for Management of OSH Inspections of Construction Sites in Lombardy

Lombardy regional OSH services use the Site Risk Monitoring System (Italian acronym Mo.Ri.Ca.) to conduct risk assessment for the planning of inspections of building sites. The system was developed as part of the National Prevention Plan for construction 2008-2010. Mo.Ri.Ca incorporates data from the regional enterprises database and data of the notification system for construction sites. Through a simple algorithm, it identifies the sites at greatest risk, based on a set of criteria and weights that were defined by the OSH services using the experience and knowledge of inspectors, fundamental physical safety elements, and assumptions about the impact on likelihood of compliance of different enterprise and site characteristics.

Given that construction is a particularly high-risk sector (as evidenced by the prevalence of occupational accidents, particularly fatal ones), and that supervision resources are inherently limited, selecting which construction sites to visit with the highest possible precision is particularly important. In particular, the criteria best predicting non-compliance, and their relative weight, need to be accurate. So far, these were based on a certain number of assumptions about the profile of construction operators, and thresholds for different risk categories were likewise set based on “common sense” discussions among inspectors – as is the case, globally, in most inspection services using risk-based approaches (which is already far superior to most services which use no risk-based planning whatsoever). At the same time, Mo.Ri.Ca. hosts results from past inspections since its start of operation, and allows to conduct several analyses, containing as it does detailed data on operators, sites (including geolocation), etc. The intent of the pilot was thus to analyse Mo.Ri.Ca’s. historical data using Machine Learning and determine the validity of the existing risk scorecard, test the predicting power of different criteria, and the appropriate thresholds.

GISA and other tools in Campania region

The Campania region has developed several IT tools aimed at supporting its enforcement system on food safety. Its initiatives have led the region to be one of the leading ones in Italy to develop good practices in technology meant to improve the regulatory delivery. The OECD, through the RAC Project, has had the opportunity to provide technical support to the most recent initiative – an online self-certification – , described at the end of this section.

The oldest tool developed in Campania is called GISA, System for the Cooperation and Management of Official Controls, created by the Region in 2007 with the support of the Higher Zoo prophylactic Institute for Southern Italy (IZSM) to support and facilitate ordinary and extraordinary activities related to food safety and public health veterinary services. New elements are constantly being implemented to allow more effective planning inspections and greater data collection and processing.

The system aims at facilitating inspections planning, preventing duplications, and promoting co-ordination between different information services and authorities involved in control activities. It involves different type of stakeholders. Local health authorities (ASL in Italian), which are *inter alia* in charge of food safety and occupational safety inspections, as well regulatory enforcement agencies involved in food safety controls different from ASL, municipal and private veterinary health and public hygiene services, universities, business associations, commons, etc., can consult and benefit from GISA and contribute to it by providing data needed for inspections.

As an integrated system, GISA has both operational and strategic functionalities that permit better inspection planning from a deontological point of view – i.e., greater health protection, and from a management perspective – i.e., using of resources. On the first aspect, GISA allows to identify different levels of risk, targeting Food Businesses Operators (FBOs) and accordingly selects proportional intervention measures. It collects, contains, and updates an FBOs census, and processes, in real time, data related to food safety inspections. Main information in this regard includes, FBOs' geographical location, risk parameters used to plan inspections, checklists, and inspections results over time. Once controls are held, the system collects information from reports and checklists, and by applying ML techniques, monitors FBOs.

From the operational perspective, GISA contributes in improving enforcement performance by providing quantitative analysis of inspections. Given quantitative and qualitative data regarding public resources and inspections means, GISA processes inspectors' performance and delivers information about optimal distribution of public resources. To define their use, the system considers geographical risk distribution and risk-based targeting of FBOs. Additional information relates to volume, types, and value of sanction. Given this information, and provided data-analysis engines, GISA can define an accurate risk-based rating of FBOs, a distribution of geographically critical areas to be inspected, an accurate geographic and risk-based distribution of public resources; and defines risk-based inspections frequency.

These functions are available to all inspectorates involved in the process, including the Police Forces. Each year the Region draws up a planning document, which is uploaded onto the system, indicating the inspection activities to be carried out during the following year. Inspections are subdivided by objectives considering high-risk targeted FBOs and geographical critical points. This way, the system automatically distributes the load of planned inspections among the various structures in charge and monitor objectives achievement.

Aside from GISA, the Campanian region partnered with the University of Naples Parthenope to develop MytiluSE, a system to predict the quality of waters to secure safety of mussels produced in the bay of Naples. The system works pre-emptively, enabling to know which days the harvesting of mussels would be unsafe. Rather than expending resources on *ex post* controls to find potential contamination, the system informs producers and guide inspectors' work by mapping contamination sources and developing a reliable predictive model. This predictive approach for mussels avoids health hazards far more effectively than inspections because microbiological testing and sampling takes time, and results may come too late (leading to potential contaminations from other products harvested the same day) (OECD, 2021, forthcoming[1]).

In addition to these instruments, the Campanian region, with the technical support of the OECD, is implementing a self-certification tool. According to the Regulation EC 852/2004, FBOs are obliged to implement food safety systems, based on pre-requisite programmes and HACCP, and to perform periodical self-control of the appropriateness and effectiveness of such systems. To provide an audit tool for self-control, the electronic form of the checklist for dairy processing facilities was prepared and will be tested during 2021. It will be accessible on the official regional veterinary inspection website where FBOs will be able to fill it and submit it to the Veterinary inspectorate. By performing thorough periodical control, FBOs will be able to identify gaps in their systems and rectify them on time. During official control, inspectors will be able to compare the results of self-control to their own findings and understand better the level of compliance of FBOs as well as food safety culture in the facility. Repeated accordance of self-control results and that of official control will indicate good understanding or food safety requirements by businesses, the parameter used for determining the frequency of official inspections. Another benefit of this kind of self-control is in situations when physical inspection is not possible (as it is the case now due to Covid-19 restrictions). Information from filled self-check lists will help inspectors have an insight into the FBOs compliance to regulatory requirements.

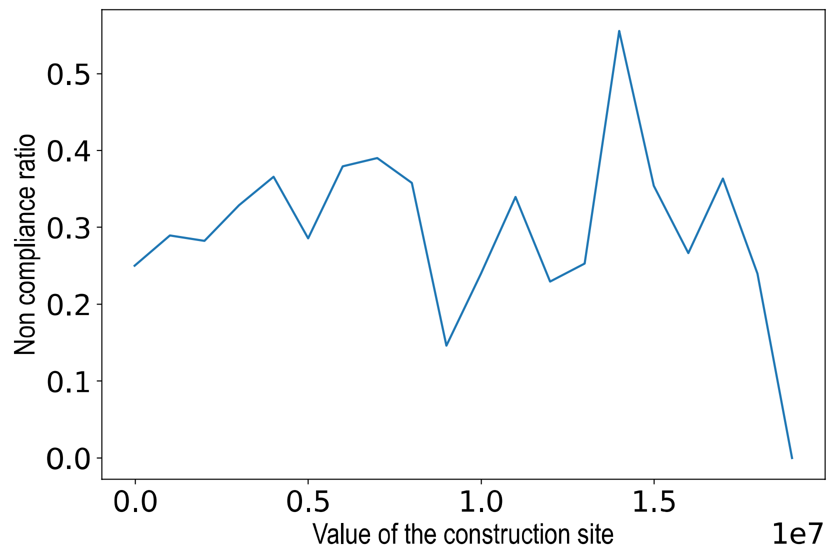
Key findings

On ML applied to OHS, the analysis covered 5 of the 8 provincial subdivisions of the Lombard system. The data sources were i) the notification of the start of construction and ii) the history of controls on construction companies and “safety supervisors”, which are operators specifically entrusted within the Italian construction system with ensuring the safety of complex construction sites. The research looked at the ability, or lack thereof, between different characteristics of the construction operators (building companies and safety supervisors), including their historical inspection records, and of characteristics of the construction sites themselves (monetary value etc.) to predict non-compliance. In particular, the research aimed at testing whether the criteria currently included in the Mo.Ri.Ca. scorecard were good predictors of non-compliance (and in the expected direction of correlation) or not, and whether the thresholds currently used for different classes were adequate or not. For example, in the score-card, the risk indicator “value of construction works” is set with a different score for different ranges of value (less than 10K EUR, 10 to 50K, 50 to 100K, and above 100K), and the research would test not only whether construction value was a predictor, but also in which direction (higher likelihood of non-compliance for higher values, or the opposite?), and at which value level(s) could a significant difference be observed. Some aspects of work typology, which are used to determine the potential gravity of non-compliances, were not tested in this first phase of the research but will be investigated in a later stage looking at the impact side of risk.

Interestingly, the research found quite diverging results for different indicators. Some of those expected to predict non-compliance were in fact essentially neutral, or very weak predictors. Others were indeed correlated with non-compliance, but in the opposite direction of what the score-card model had expected. Others again were adequate predictors, but the thresholds chosen in the scorecard were inadequate (i.e., did not correspond to inflexion points in the non-compliance rate curve). Finally, some were good predictors and in the correct direction, but the research was able to suggest better ways to formulate and measure them. We provide a couple of examples below for illustration purposes.

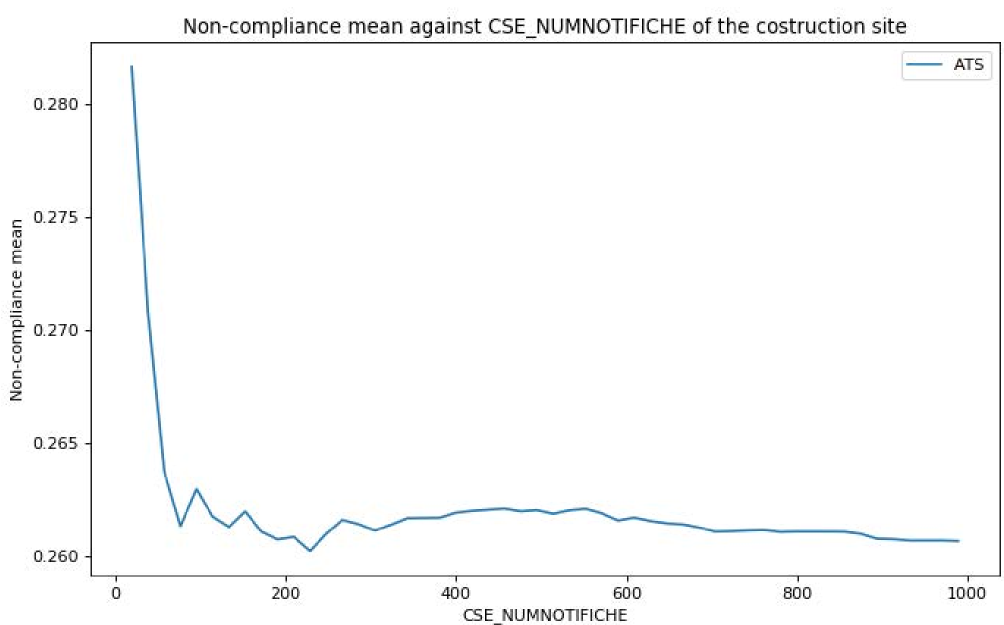
The total value of the construction site was found to be a very weak predictor of non-compliance, with non-compliance varying in a somewhat random way in function of the monetary value – and thus does not appear to be a very usable or useful indicator for risk-based targeting (see Figure 2.1)

Figure 2.1. Variation of the construction-value predictor



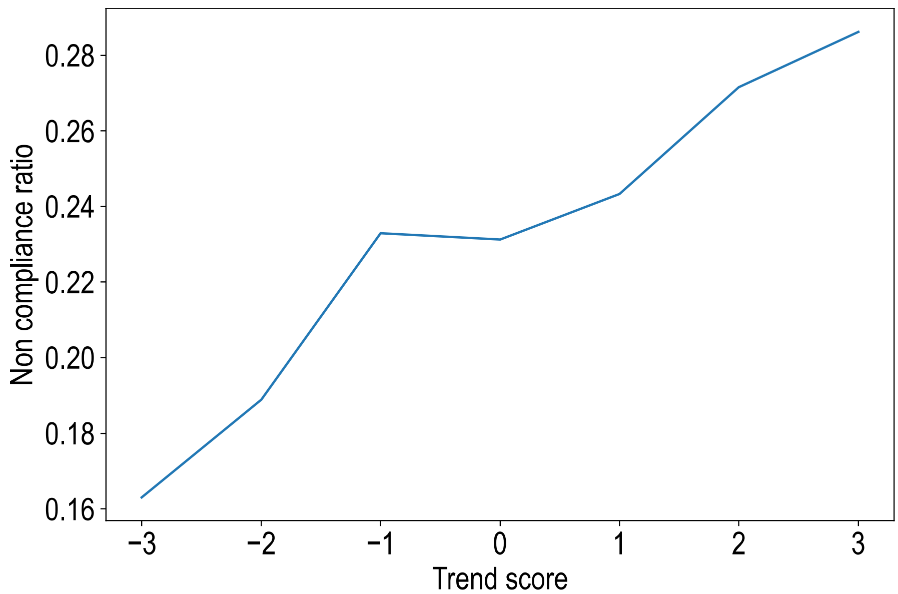
The number of sites supervised by one and the same safety supervisor, which was expected to be a predictor of non-compliance by the scorecard (the assumption being that supervising too many sites would lead to lack of attention to each), was in fact found to work in reverse. Having a safety supervisor in charge of only one or very few sites was found to be a very strong predictor of non-compliance (possibly this would correspond to people or companies with little experience or a bad reputation) – whereas above a certain threshold the curve is close to flat (i.e., the threshold effect is very strong, and there are just two categories).

Figure 2.2. Record of non-compliance



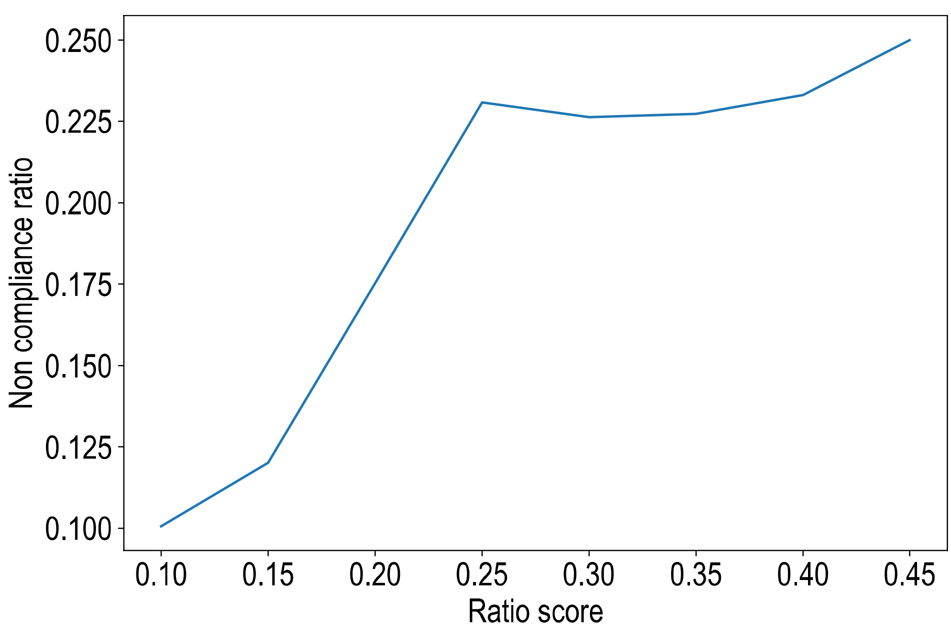
The previous record of compliance or non-compliance, on the other hand, proved to be a strong predictor in general – but different ways of formulating and measuring this track record yielded more-or-less strong results. Simply looking at the result of the last inspection was not the most meaningful indicator. Considering the average of non-compliance vs. compliance findings across all previous inspections of one company gave much better results, but with some "instability" in the overall trend (curve with two inflexion points, i.e., at one point the indicator was functioning "in reverse").

Figure 2.3. Non-compliance trend



The best predictor was found to be the trend of (non-)compliance, i.e.

Figure 2.4. Non-compliance historical ratio



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OECD (2021, forthcoming), *OECD Regulatory Policy Outlook 2021*, OECD Publishing, Paris. [1]

3 The RUCP system and the RAC engine in the Autonomous Province of Trento

This chapter presents the functioning of the RUCP with the RAC engine in Trento Province. Originally conceived as a single register holding data from different inspectorates, the RUCP is now evolving into a system designed to perform risk analysis by segregating businesses as per risk classes and levels. RUCP uses the internationally accepted scorecard tool to estimate risk-based ratings of operators. The chapter also delves into the technical realm and explains the system architecture and the process that goes behind RUCP's output delivery. The chapter illustrates the system application through the example for an environmental risk assessment for a business holding environmental authorisation. Three regulatory streams i) environment ii) labour iii) agriculture payments, show the areas in which the RAC engine can be developed and also the areas in which data-based analysis can be used. Finally, the chapter notes current limitations in data and recommendations for the future.

Introduction

The RUCP was created to be the single register of the inspections conducted in the Autonomous Province of Trento. It is not yet fully operational, but a pilot on agriculture payments inspections has been performed. It is meant to function with data collected by provincial agencies and inspectorates regarding their enforcement activities, and data related to objective characteristics of businesses. To do so, the RUCP draws information from the chamber of commerce database (C.C.I.A.A., Chamber of Commerce Registry) and other sources related to specific activities such as construction (i.e., CNCPT database[1]) and goods and services certifications (for instance, Accredia[2]).

When first conceived by the regulator, the RUCP was envisaged to support inspectors on providing reliable data to better plan activities. Additionally, it was meant to prevent overlapping and duplications among inspectorates. Yet, following an initial assessment within the RAC Project, it was concluded that a punctual definition of the RUCP and its functions was needed. For this purpose, an Inception Deck methodology was implemented.[3]

As resulted from the Inception Deck, it was decided that the RUCP would become a system – not only a register – with the RAC engine inside, capable of i) delivering a risk-based rating of companies; ii) validating existent risk parameters; iii) defining new risk parameters. Accordingly, the RUCP will be able to deliver the following outputs: i) display for each enterprise the risk classes calculated according to fields in which it operates; ii) represent the impact-likelihood of each company, possibly by showing the risk matrix; iii) extract a list of businesses organised according to their risk level; iv) develop a function that enables an easy selection of business groups organised according to their risk level.

The RAC engine is able to deliver risk-based rating of businesses if existent risk parameters in the form of scorecards are first provided (see Box 3.1). Once the parameters are provided, the tool will process the existing knowledge and perform predictive modelling (OECD, 2019[1]) (OECD, 2020[2]).

Box 3.1. Using scorecards on data-based risk analysis

Relevant international experiences show that the most used tool aimed to define a risk profile is the "scorecard", i.e., a list of – legal and technical – parameters formulated to assess businesses' compliance weighted on the risk they represent. This way, scorecard allows to associate the potential risks for a company with a score in a very simple way. Since risk assessments have no straitjacket approach and need to be tailor made in the context of the specific risk and risk factors, activities and policies when assessed and scored against predetermined parameters can help identify high risk operations and set priorities.

The scorecard is widely used not only because of its advantages in defining companies' risk profiles but also due to their simplicity. Beyond defining risks, scorecards are also remarkably useful for their benefits on machine learning processes aimed at calculating probability of risks. Scorecards indeed facilitate the procedure of calculating a risk score by providing a defined risk used by the ML algorithms to multiply the probability that the risk becomes concrete and the potential impact (damage) that may occur.

In order to better utilise the European Structural and Investment (ESI) funds and to protect it from potential fraud and corruption, the OECD has provided targeted guidance to authorities in Slovak Republic through data driven approaches to risk assessment and a systematic approach to managing these risks. The importance of enhancing the use of Arachne risk-scoring tool by authorities to refine risks has also been prioritised.

Based on the scorecards inserted into the system, the engine applies the algorithms aimed at identifying businesses characteristics and assigning them a non-compliance level of risk. Once the features are identified and risk labeled, they will be analysed through another type of algorithm (a linear algorithm) to produce a risk prediction based on the probability estimated with ML. During this process, particular attention has to be paid to i) the features interaction in order to avoid bias[4] (e.g. linear independence where there is none); ii) being flexible on the prediction of likelihood of non-compliance. The algorithms, thus, must be customised and validated to obtain more certain and accurate predictions. With the support of the Department of Information Engineering and Computer Science of Trento University initial research is being done to define a sort of validation mechanism of the algorithms (see Chapter 4).

The system architecture: the risk calculation process and the risk assessment

Risk calculation process

As mentioned, the RAC engine delivers a rating of businesses according to a given level of risk by applying algorithms to data and scorecards available on the RUCP. The risk calculation is the process devoted to such output, and consists of different phases: exportation of the data, data preparation, prediction, UX which is the actual usage of the risk classification:

EXPORTATION → PREPARATION → PREDICTION → UX

Exportation*:* The exportation concerns the transfer of information from available databases to the RAC Engine. The IT systems that contain the data needed to perform the risk assessment are extremely heterogeneous. A good part of these systems is managed by Trentino Digitale (TD, IT public company of Trento), but there are also solutions acquired from different suppliers, in some cases even outside the TD datacenter.

The process requires to convert data into csv file[5] in order to prepare it for cleaning, as described in the next step. Such a host will organise information to create scripts (bash, sql, python, etc.). The scripts are then processed by a pipeline software to enable them to download the csv file, clean, aggregate/organise, classify the risk, and provide an output. The proposal mainly focuses on scripts for two reasons: make the system development process simpler without implementing advanced algorithms by data scientists; grant more flexibility in developing the model. The model allows direct access to data when it is managed by TD. Otherwise, it should be foreseen an exportation, for example, by HTTP. The output of this phase is the disposal of data in the system ready to be used by the algorithm.

Data preparation: This phase is dedicated to clean and aggregate data in a single csv file. Here are included all the lines concerning the characteristics to consider in the companies' risk assessment. This stage also covers data denormalisation[6] from multiple tables and the dataset reconstruction in a convenient format for the algorithm. The output of this phase will therefore be a single dataset per area, with a row for each company, showing all and only the characteristics used for the calculation of the risk class.

Prediction: Finally, an algorithm for the risk evaluation combines the companies' characteristics providing a numeric result. Such a number is then converted in a risk class by using thresholds. To do so, the algorithm takes the csv dataset file of the characteristics as input, and for each row calculates a numerical value that can be interpreted as a risk level. Through defined thresholds this is converted into a label (e.g., low, medium, high). The work is delegated to a script that will perform these steps: i) Reading the characteristics of the company from the csv file; ii) Multiplication by the weight vector that represents the algorithm; iii). Identification of the risk class based on the defined thresholds. The output of this phase is a risk value associated with the company in the RUCP system.

In some circumstances, Machine Learning techniques have been applied for the construction of the algorithm, which may be refined from time to time with new data, according to a frequency that could be annual. The algorithm is the result of the analysis of company data, and of the parameters suggested by the experts.

UX: The risk classification is ready to be used by the operators (inspectors). To this end, the inspector shall be able to access at least the following information: the risk class assigned to a company for each field in which it operates; extract a list of companies classified by their level of risk and field. The output of this phase is a sample to planning inspections.

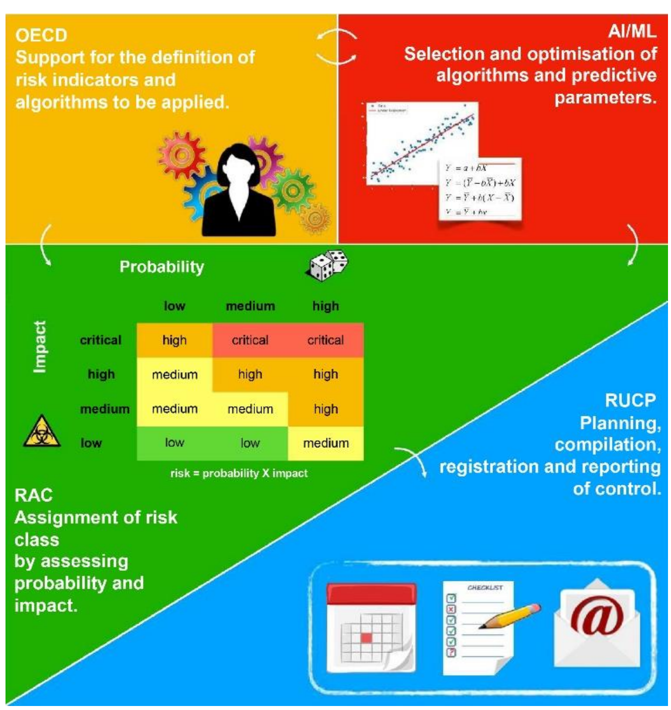
Risk assessment

For the system to retrieve the businesses characteristics, assess their risk, and execute the risk prediction two algorithms are needed. One which provides a risk rating list of the companies. This algorithm could consist of a software code developed within the RUCP system itself or with an external service. The second, driven by the rating provided by the first one, should extract and propose a list of businesses to investigate. Also, this algorithm should process systematic criteria.

Businesses' risk is assessed by evaluating their historical behaviour based on previous inspections and considering the fields in which businesses operate. In this regard, the calculation of the risk class of a particular company is different for each area in which it is involved. Therefore, the same company may have an assessment under the environmental point of view and, at the same time, another evaluation for the work safety one, for instance.

The RAC Engine will provide a final risk assessment without performing any differentiation among the two components: i) the historical behaviour of the business and the probability that the way it acts is liable to non-compliance; ii) the objective risk characteristics related to the activity itself. A sum combines these components. The mathematic operation used keeps the system considerably simple. Figure 3.1 represents the RAC Engine.

Figure 3.1. RAC Engine



When assessing businesses' risks three aspects are considered: business characteristics, probability and impact characteristics, systemic criteria.

Business characteristics: A rating tool must be able to make predictions by leveraging several business characteristics. For convenience, these have been divided in three categories: general features, which are common to all enterprises (i.e., size of establishment or number of employees); specific factors linked to the type of activity of the enterprise (i.e., treating toxic or polluting products); management characteristics related to "how" the enterprise has been managed (i.e., certifications or control assessments).

Those data on characteristics need to be automatically collectable and updatable, using the abovementioned web services where possible (i.e., Chambers of Commerce).

Probability and impact characteristics: These include both characteristics that will have a predictive weight for the probability and impact of the risk. For a risk assessment on knowledge-based weights (i.e., a scorecard proposed by an inspector), this second classification is not relevant. If Artificial Intelligence (AI) and ML criteria can increase predictive efficiency, it is necessary to address the following issue. The target characteristics to train supervised algorithms are limited to the aspect of probability: there are precise measures of non-compliance, but there are none related to the impact that such "non-compliance" may produce if an accident occurs. What is relevant for the implementation of the ML algorithms is that the features that would be used in the predictive model of the probability of non-compliance will be included in the trained model and will inherit their weights from it. Moreover, the impact-related features will continue to have weights defined by the expertise of specialists (inspectors). Furthermore, the determination of the risk rating will depend on an additional combination criterion i.e., a linear combination or a risk matrix.

Systemic criteria: The systemic criteria help the RAC Engine to select companies to be investigated. Those are not necessarily related to the determination of risk. The most effective choice to perform a certain number of controls and find the most significant number of nonconformities is to inspect the companies with the highest rating.

Box 3.2. Example of the system application

Below is a representation of an environmental risk assessment for businesses holding environmental authorisation (called "AIA") to release specific quantities of pollutants into a reservoir. The hypothesis assumes the used of the following values:

Toxicity of the substance (T) Quantity of pollutants allowed (V) Reservoir critical issues (C)

The designed model foresees that potential risk is calculated using this formula:

Potential Risk = C + T x V

The system uses two thresholds to set up three risk levels (Low/Medium/High).

To evaluate the probability component of non-compliance of a business, we take into account two values:

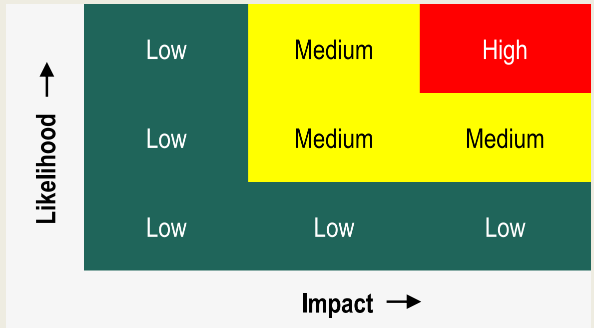
- The average of times in which it resulted in non-compliance during previous controls (R);
- Last checks differential (D)

In this case, we foreseen a linear algorithm derived from a regression (machine learning) to set up the potential risk class. Again, we assume three risk levels (Low/Medium/High).

Probability of non-compliance = w0 + R x w1 + D x w2

Finally, let us assume that the final assessment is calculated by applying this simple risk matrix (3x3)

Figure 3.2. Model of a risk matrix



Issues in the selection of companies such as: non-compliant selection,[7] uneven distribution, not compatible with the resources needed, and inconvenience may occur. Those circumstances inevitably lead to a loss of effectiveness. Thus, they must be anticipated. Yet this cannot be addressed by an artificial intelligence algorithm, and must therefore be developed in software, following a more traditional methodology.

Key findings

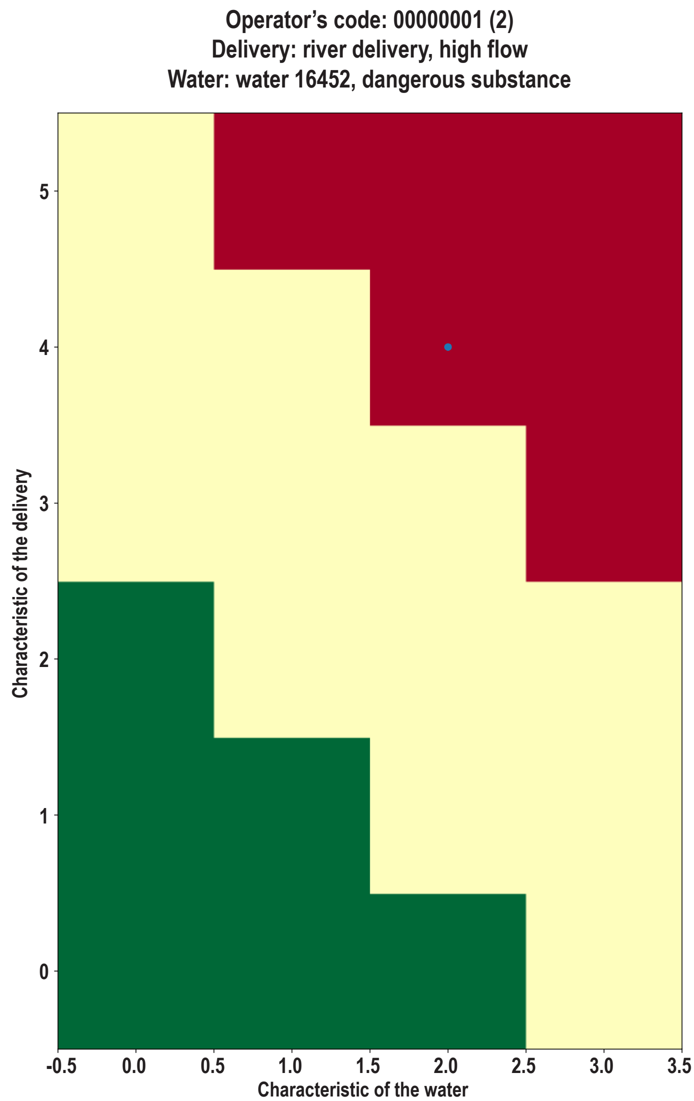
Regarding the RUCP system and the development of the RAC Engine the pilot initially involved the assessment of five areas of inspections and their IT tools: OSH, food safety, environmental protection, agriculture payments and labour law. The research looked at the available data and its potential to be processed by the RAC Engine. The analysis revealed that just three of them (environment, agriculture payments and labour law) would be able to dispose their data to activate the process. While the data from these three inspectorates was indeed managed by TD (Trentino Digitale, public IT company from Trento) the other two agencies (i.e., OSH and food safety) have their own databases with privacy (legal) restrictions to export data into RUCP. The RAC Engine is therefore first oriented to deal with the inspectorates with data managed by TD. The export phase in the future, cannot be managed in a uniform manner for all these systems, the strategy must guarantee a certain uniformity, while imposing the least number of technical constraints. For the remaining inspectorates the exportation phase of the calculation risk process becomes easier to perform. This way inspectorates can fully integrate, streamline and digitalise the audit activity.

Yet, even in these cases, some relevant information remains outside the process. Unfortunately, information from control results are not always properly digitalised and systematised but continue to be pure text files, difficult to analyse. Because of this, just a few of the existing data is useful to elaborate risk ratings and to perform risk assessment through ML techniques at this stage.

However, limited availability of data has not prevented the pilot from achieving significant results. In the environmental protection stream, a risk assessment is being implemented using insights from the IMPEL model[8], and available data regarding the objective characteristics of the businesses and the intrinsic risk of their activity (i.e., the potential to produce environmental harm given the toxicity of the substances managed by a given company, the correspondent volumes by it spilled, and the reservoir where the spillover take place). The behavioral history of businesses is not being considered in the assessment since, for now, information that can be used as data to activate the RAC Engine is not available. In the future, the service intends to collect inspections record in a more systematic way, which will allow to use the "behavioural history" of the business as one of the risk criteria in the RUCP. In the meanwhile, the possibility of using information related to fines and sanctions is being assessed. Besides this situation, current data allows a basic risk assessment and is useful enough to provide a risk-based rating of businesses.

Figure 3.3 shows risk assessment for a given company in terms of water pollution. The X-axis represents the reservoir in which the discharge occurs, while the Y-axis represents the volume of water exposed to pollution. Once the information related to the level of discharge and to the volume of the toxic substance is submitted into the system and given specific parameters of risk and scorecards, the RAC Engine applies the algorithms and performs a risk analysis delivering a specific level of risk for the given company. In the graph it is represented by the little blue point, which according to the calculation, is located at a medium level of risk represented in the figure by a yellow stripe.

Figure 3.3. Risk assessment on environmental protection



The same data used for the rating is being analysed with ML techniques to define the accuracy of the existing scorecards or to produce new risk parameters. Both are later used to choose samples for planning inspections, and to elaborate checklists for on-site inspections. On these bases the pilot is proving to deliver important results to improve regulatory and enforcement systems on environmental controls.

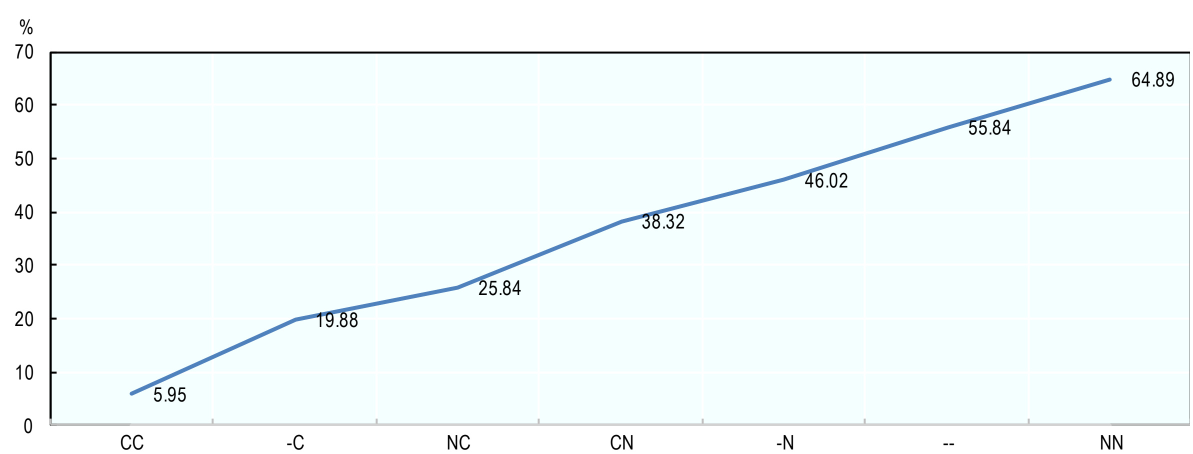
On the labour law stream, data-based analysis is mainly being directed to explore a validation mechanism of the algorithms. To assure the accuracy of a predictive method such the RAC Engine, it is necessary to agree on a sort of validation mechanism. In the first instance, the validation is generally to be found in the expertise of the inspectors who provided the scorecards. Drawing on this, AI and ML techniques are applied seeking to answer the following questions: i) How a chosen algorithm can be validated? ii) How its effectiveness can be measured? iii) How it can be optimised? The answers come from the data analysis. Using historical data, the scorecard is analysed to determine its degree of effectiveness. Interestingly, much more can be done. Through data preparation works, new characteristics of the business – which were not taken into consideration before – can now emerge and provide potential information regarding the companies' level of risk.

The inspectorate in charge of labour law enforcement provided a significant set of historical data, later used by the Department of Information Engineering and Computer Science of Trento University to initiate a research, through a degree thesis work, on ML applied to prediction: With automatic learning, new combinations of characteristics and weights can be searched and measured in effectiveness, until they converge to the optimised algorithm. Then this algorithm can be also used within the sample extraction software, e.g., RUCP (or even with pen and paper) to define the companies that will be inspected according to their risk profile. Over time it is also possible to continue supervising the effectiveness of the algorithm predictions, giving positive or negative reinforcements depending on the success or failures of the predictions. Periodically (for example every year) it is possible to reprocess the data by adding new ones, to refine or update the algorithm.

The research developed with Trento University analysed the features already present inside the labour law inspectorate's application (called SISL in Italian) aiming at studying which combinations of companies' characteristics are more effective for predicting compliance levels. In doing so, also many algorithms were tested and their performance were compared. The thesis was therefore very useful to provide a first analytical glimpse of the original dataset. Drawing upon these results, the OECD Team produced some preliminary data interpretations that, after being shared and discussed with the Labour law inspectorate, gave place to the creation of better indicators starting from historical non-conformities. With an approach partly similar to the one developed for OHS in Lombardy, the OECD studied the impact that the compliance trend of the last previous inspections has, and found the linearity expressed in Figure 3.4, where C correspond to compliance and N to non-compliance.

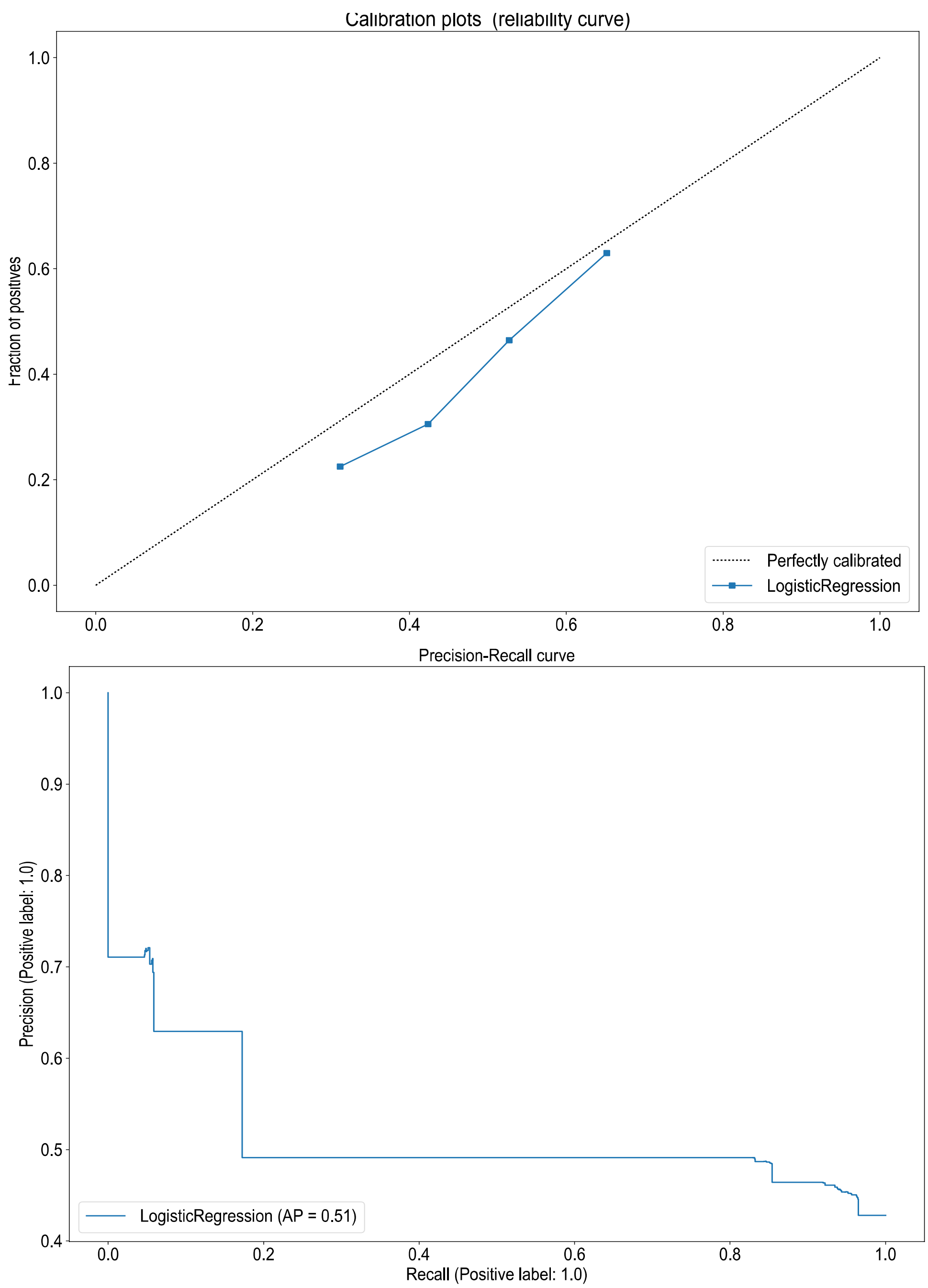
Figure 3.4. Compliance trend analysis on labour law

Second-last	C	-	N	C	-	-	N
Last	C	C	C	N	N	-	N
%	5.95%	19.88%	25.84%	38.32%	46.02%	55.84%	64.89%
Score	**0**	**0.1666**	**0.3333**	**0.5**	**0.6666**	**0.8333**	**1**



The algorithm provides a positive prediction, and indicates how reliable it is, i.e., it indicates its degree of certainty on the prediction's accuracy. On well-calibrated models, the "algorithm confidence" varies in the same way that the probability of the prediction's correctness does. Thus, whenever predictions with "greater confidence" are taken, the likelihood of correct predictions is greater as well. The analysis for the labour law inspectorate allowed thus to create a strong feature which, combined with the others in a logistic regression algorithm, increased the precision of the non-conformity control prediction to almost 50% (see Figure 3.5).

Figure 3.5. Algorithm calibration



Due to the characteristics of the chosen (calibrated) model it was possible to rely on the confidence algorithm to extract a given percentage of companies to be controlled, on which the precision rose to 61%, extracting 10% of the companies, and to 66% extracting 5% of businesses.

Though the results are not yet finalised, and the OECD Team continues to develop this pilot, evidence show the advantages of customised algorithms to correct predictions and review risk parameters. It has been possible to define the general characteristics of the machine-learning model, and its integration into the system. Due to the impossibility to inspect all the companies, and the need to identify a limited sample of businesses at risk, it becomes imperative to assure the highest degree of "confidence" of the algorithm. For this reason, it is advisable to use calibrated classification models.

Notes

[1] The National Commission of Territorial Joint Committees managed a database related to construction sites and occupational safety measures.

[2] Accredia is the body designated by the Italian government to certify the competence, independence and impartiality of the bodies and laboratories that verify the conformity of goods and services to the standards.

[3] The OECD Team adopted a tool called Inception Deck to map, along with the IT company from Trento, Trentino Digitale, all the project's boundaries and the RUCP functionalities. Such a method foresees a set of ten slides defining the proposal's expectations by the stakeholders' points of view, the focus points, the criticalities, a roadmap and a first blueprint of the system's architecture.

[4] For these purposes bias are assumptions in the machine learning process that generates results systemically prejudiced.

[5] CSV File: Comma-separated values is a text file in which all values are separated by a comma. The csv is a standard and wide used format for data in Machine Learning.

[6] Meaning having a single dataset with all the information replicated that can be used by the algorithm.

[7] The optimal sample from the risk profile may not coincide with legal prescriptions aimed at defining the sample in a certain way.

[8] The Impact Management Planning and Evaluation Ladder (IMPEL) model is the most extended method used by European Union member states to perform risk-assessment on the environmental protection stream.

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4 Lessons learnt

This chapter lists out the lessons learnt and the key challenges to an increasingly “first choice” approach to regulatory delivery. Problems related to data integration into a single register, reliance on third parties for automatizing solutions and updating of risk classes in a timely interval would have to be resolved. Legal and administrative hurdles also place hindrance on the development of IT tools. In addition to this, IT systems need to fillip the real goals of regulatory delivery – risk management and reduction, to ensure a meaningful protection of key elements of the public welfare – than just weeding out non-compliant actors. The report ends with reference to the guidance existing OECD toolkits and frameworks that can be used in resolving these issues.

Research is ongoing and these pilots are showing that, given the increasing availability of computerised historical inspection records, and the decreased entry barriers to apply Machine Learning techniques (growing availability of skills and software, decreasing cost of computing power), using such an approach to improve risk-based targeting can now be considered a “first choice” approach. Except when historical records are unavailable (or recorded in a way that cannot be processed easily, i.e., pure text files, which require a more complex analytical process), conducting such type of research is clearly possible, not overly costly, or complex, and can provide significantly better results than more “traditional” approaches based on heuristics and on experience of inspectors and outside experts. The ability of an individual to make decisions can often be impaired by the quantity of data required to be processed. That said, professional experience, of course, remains highly relevant, and in combination with Machine Learning, will define the assumptions and questions that quantitative research will put to test. In the future, with the cross-functional applicability of data and greater uniformity in the manner in which data is governed, risk identification and classification can be better performed.

There are, however, different challenges and limitations pertaining to this computer-assisted approach. Regarding the RAC Engine and the use of algorithms applied within a single register a main challenge is to integrate the data in one only repository so to apply the algorithms needed for the risk assessment. The exportation process of data into the single system might be addressed in different ways and depends on the future of the software which the data is coming from. Yet, if the solution cannot be automatised the work of an operator might be required. In the worst-case scenario, an export request to the software house that developed the software might be needed. Additionally, the frequency of the risk classes might be distorted. While available data on the system allows to update risk classes and businesses risk-based rating often, the frequency of the risk classes definition would depend on the availability of the data to be exported from other software. In these situations, it will be possible to choose a frequency for the definition of the six-monthly or annual risk classes. Moreover, for some regions, legal constraints and juridical interpretations of privacy regulation and data protection norms entail further barriers for data exportation and data sharing. Holistic data governance frameworks should be designed to ensure the proper management of data through its entire life cycle. A uniform framework would also help in achieving transparency and privacy goals across the cross functional regulatory purposes that a given set of data serves (OECD, 2019[1]).[1]

On the ML domain the first challenge is the greater difficulty in assessing factors predicting the “impact” dimension of risk (how much damage is done by non-compliance), because detailed data on this aspect is often missing, or indirect (registering the type of non-compliance, but not necessarily allowing to link to actual damage).The second is the fact that following only the predictors suggested by the algorithm would cause inspections to focus only on the cases where the likelihood of “catching” non-compliances is the highest, but this would not correspond to the actual goals of the regulatory system, and must thus be balanced by other elements to provide an adequate targeting system. We briefly develop these two points below.

The likely “impact” of non-compliances, which is a necessary data point to build a fully data-driven risk model, is often missing from inspection records. Indeed, in many cases these register only the administrative decision taken, without details. In better situations, they also record the exact points of non-compliance, but there is very rarely any data that could directly point to harm (e.g., record of accidents etc.), so that the analysis of impact must rely on assumptions about the impact of different types of non-compliances (i.e., on expert opinion, essentially, even if grounded in science etc.). Future efforts would focus on the value such data has created in risk management and in absolute terms of number of lives saved, accidents avoided, etc. Still, there is much that can be done using such data, and this will be the subject of further stages of this pilot research, to see if good (improved) predictors can be found not only for “non-compliance” in general, but for the severity of non-compliance as well. Such work will in any case remain more difficult and more tentative and uncertain than simply predicting non-compliance.

An additional challenge is created by the difference in goals between the model defined through Machine Learning (predicting the highest possible percentage of non-compliances, i.e., ideally targeting inspections so that 100% of them reveal non-compliances), and the regulatory system – which aims at managing and reducing risks, i.e., overall, at reducing non-compliance, and must consider not only the "known" targets, but the "unknown" ones. If we take the example of OSH inspections in construction sites, there are always several companies (construction companies, safety supervisors) which are new to the market, and thus "unknown". In the score-card model, and in line with usual risk-based practice, the regional OSH services have assigned a certain level of risk to these "unknown" operators (rather than zero), to ensure that a certain number of them are targeted. The "pure" Machine Learning model would, by contrast, exclude them since they are (by definition) not known. Thus, a first point is that it is essential to balance the data-driven model by a percentage of selection that covers uncertainty and unknowns. Experience also suggests that, because fraud, dissimulation, or errors in data etc. are all possible, a small percentage of inspections should also target objects that the model would classify as "low risk", just to ensure the system's robustness and check that there are no significant "leaks" in the risk-assessment system. Finally, selection based on likelihood of non-compliance is only a component of a good risk-based, outcomes-focused regulatory delivery system. Taking a higher view, the system should aim at reducing non-compliances, and thus (in good circumstances and/or in regulatory areas or sectors where non-compliances are less frequent etc.) planning based on non-compliance predictors may be less useful in certain contexts (where, on the contrary, potential impact may be more important).

Inspections' experience suggests that implementing effective inspections strategies requires to address several complex challenges simultaneously. The OECD Regulatory Enforcement and Inspections Toolkit (OECD, 2018[2])) offers government officials, regulators, stakeholders and experts several criteria to assess the inspection and enforcement system in a given public structure headed to address many of these challenges. IT solutions such as the RAC engine and the Machine Learning tools could significantly allow for a better implementation of the Toolkit recommendations with greater results on regulatory delivery. Challenges related to staff training and digital capacity building are gradually improving. As technologies advance, more than digital literacy, "21st Century Skills" are required. Digital government user skills require public servants to recognise the potential for digital transformation, understand users (society) and their needs, collaborate openly for iterative delivery, use data trustworthily and support data-driven government (OECD, 2021[3]).

The Italian pilots has shown so far that the ranking of economic activities under specific risk classes and the prediction of non-compliance likelihood are more data evidenced than those produced without IT techniques with several advantages. Correctness of predictions and accurate targeting of risks allows for more proportionate and responsive approach. The use of an automated system grounded on transparent criteria corroborates clear and fair procedures. Leveraging on technology when implementing and enhancing risk-based inspections increases regulatory delivery levels. Yet, the use of IT in the enforcement process does not mean a replacement of the inspectors and the human volition. Inspectors' decisions lie upon the very core of the inspection activity and the enforcement process. It is only the inspector who can raise disputes in line with applicable rights and professional obligations. IT tools are used in this context to better address their actions towards risk. Future endeavors, based on current learnings, would also focus on training inspectors and empowering them to better apply IT tools, while simplifying the process using intuitive dashboards and interfaces so that those without adequate data experience can also benefit from improved technologies.

Note

[1] See specifically Chapter 2, https://www.oecd-ilibrary.org/sites/9cada708-en/index.html?itemId=/content/component/9cada708-en.

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Data-Driven, Information-Enabled Regulatory Delivery

Industries and businesses are becoming increasingly digital, and the COVID-19 pandemic has further accelerated this trend. Regulators around the world are also experimenting with data-driven tools to apply and enforce rules in a more agile and targeted way. This report maps out several efforts undertaken jointly by the OECD and Italian regulators to develop and use artificial intelligence and machine learning tools in regulatory inspections and enforcement. It provides unique insights into the background processes and structures required for digital tools to perform predictive modelling, risk analysis and classification. It also highlights the challenges such tools bring, both in specific regulatory areas and to the broader goals of regulatory systems.

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