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How CIs can Tackle Future Pandemics A Multi-Domain Approach to Improve CI Resilience

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***Abstract*—In this paper, we present an integrated approach that combines data and information sources from different domains to better capture the potential effects of a pandemic and to improve preparedness of critical infrastructures and decision makers in the future. This approach not only takes epidemiological data on a pathogen into account but also allows to simulate the cascading effects of the pandemic itself as well as the mitigation measures might have on the operation of CIs from various domains and, consequently, on the well-being of the society. Additionally, these effects can influence the operational capacity and economic well-being of CIs. Hence, the approach also projects the possible economic effects, i.e., monetary costs, a future pandemic might impose on society, including wide-ranging counter measures such as school closures or lock-downs.**

I. Introduction

UNLIKE any other event, the COVID-19 pandemic has shown the complex and highly sensitive interrelations among the society, the critical infrastructures (CIs) and the decision makers on a national and supra-national scale. The pandemic not only had a huge impact on people's health as well as on public health but also on the functioning of critical services and thus on the social well-being of a large part of the European population. Additionally, the measures taken to mitigate the pandemic, ranging from social distancing to complete lock-downs, came with huge challenges and high cost for CI operators and national governments. From pandemic plans existing before COVID-19, it becomes evident that such wide-ranging effects and large-scale impacts were not foreseen by decision makers. However, similar pandemic events will become more likely in Europe in the future, particularly when considering climate change [4]. Hence, it is of utmost importance to prepare decision makers, CI operators and the society as a whole for future pandemics to increase their individual and combined resilience.

As part of this preparation activities, the SUNRISE project [29], funded by the European Union in the course of the Horizon Europe Programme, aims at developing a comprehensive strategy for CI operators as well as national and regional authorities to improve their robustness and resilience against future pandemic scenarios. To achieve that, the project focuses on the integration of several simulation approaches and tools from different domains such as health and epidemiology, regional and national economics as well as general aspects of CI protection. This integrated approach provides a holistic overview on the current pandemic situation to decision makers on a regional and national level as well as to CI authorities and operators.

In this paper, we will give a first insight into this integrated approach and present its overall methodological setup, i.e., the SUNRISE Process. This process represents a step-by-step guideline for CI operators and decision makers from regional and national authorities on how to prepare for and tackle an upcoming pandemic. We will show how the process utilizes data sources from different domains (i.e., epidemiological data on the pathogen, structural data on the CIs relevant for or affected by the pandemic as well as data on economic effects of the pandemic) and combines them into a decision making framework. As an example, we will also describe three simulation tools, one for describing the spreading of a virus during a pandemic, one for indicating the cascading effects of the pandemic across various industry sectors and domains and one for capturing the short- and mid-term economic effects on individual sectors.

The rest of the paper is structured as follows: in the next section, we provide a short overview on related work on pandemic preparedness and approaches to increase the protection and resilience of CIs during a pandemic. In Section III, we describe on a high level the SUNRISE approach and the different process steps that CI operators can use to increase their resilience. As these steps are driven by ICT tools, we show some examples of simulation tools in Section IV, which can be used – and combined – to obtain a better overview on the effects of a pandemic on the CIs, the economy, and the society as a whole. Finally, Section V concludes the paper and provides an outlook on next steps in the project.

II. Related Work

Critical infrastructures (CIs) are interdependent in many ways. First and foremost, CIs provide goods and services that are used by other CIs, e.g., a hospital needs electricity and water for operation, but also depends on the transportation system for staff and medication. In recent years, digitalization induced further dependencies, e.g., by electronic control systems for physical processes. Due to these interdependencies, CIs cannot be treated as isolated entities. In particular, any risk analysis carried out by an individual CI needs to take the interdependencies with other CIs into account, since those relations affect the operation of the CI itself. Furthermore, when looking at the complex network of CIs within a region or on a national scale, it is important to consider this entire network of CIs because the interdependencies affect not only risk level (i.e., the impact of particular threats on all CIs) but also the resilience (i.e., how fast all CIs can recover from an incident) of the entire network. Hence, many approaches to analyse these cascading effects such as the Cross Impact Analysis (CIA) [31], the Hierarchical Holographic Model (HHM) [9], Input-output-Interoperability Model (IIM) [23] or approaches using Interdependent Markov Chains (IDMCs) [32] have been developed. More specific models are focused on the coupling of two different domains, e.g., a power network and an ICT network by a co-simulation approach [6].

Apart from analysing cascading effects, a major challenge is to feed their consequences into the CIs' risk and resilience management. Although resilience concepts have been discussed for power distribution [18], railway transportation [5] and water distribution systems [28], amongst other sectors, they do not sufficiently address cascading effects. Recently, a combined risk and resilience management process has been proposed using a cross-domain simulation approach to integrate the consequences of cascading effects [25]. However, this process is highly generic whereas more precise guidelines for CI operators and authorities are required, tailored to the complex and wide-ranging effects of a pandemic.

A pandemic is usually assessed in terms of its effects on individual and public health, mostly by analyzing disease burden and excess mortality. For example, during the COVID-19 pandemic epidemiological and modeling studies were able to assess early on the direct disease burden by providing data or estimates on potential unreported cases [33], transmission parameters [2] case fatality and number of deaths and expected population mortality [21] and potential health care burden such as bed capacity pressures in ICU and hospital wards [11]. Nevertheless, the actual disease burden and expected excess mortality during the COVID-19 pandemic depends on more than these estimates. In a conceptual model, other dependencies would include the direct COVID-19 burden (as described above), the indirect COVID-19 burden resulting from pressures on health system capacity other disease burden due to economic effects of the pandemic/the response to the pandemic as well as other disease burden due to social distancing as a result of the pandemic or the response to the pandemic [7]. Hence, the effects of a pandemic cannot only be assessed from a epidemiological perspective but need to include a broad variety of domains and thus need to cover a multiple impact categories.Thus, even just for the critical infrastructures of health care effects and impacts from domains beyond simply pandemic spread have to be considered. Besides healthcare systems, CIs in general are at high risk of destabilisation by both pandemic spread and anti-pandemic measures [26].

Regarding the consideration of interdependencies in (macro)economic analyses, a wide range of different models has been used for the economic impact assessment of different types of disasters. Most commonly, economic measures are applied to quantify the relations between CIs and other sectors. Inoperability input-output models (cf. [27] allow for a reduction of the operational level if intermediary inputs are not available. Other approaches may for example take Computable General Equilibrium (CGE) models or network approaches [30] into account, each with different advantages and drawbacks (cf. [17], [8], [16]). Alternatives might look at CIs as individual agents, interconnected by a set of relations. This perspective allows applying agent-based macroeconomic models developed for assessing the impact of natural disasters [3] or pandemics [20] to CIs, too.

III. SUNRISE Process

The SUNRISE approach is described in the form of an iterative, step-by-step guideline, i.e., the SUNRISE Process, describing the individual activities that can support CI operators in increasing the resilience of their respective infrastructures. The SUNRISE Process is based on existing principles and standards such as the PDCA (Plan, Do, Check, Act) Cycle and the International Organization for Standardization (ISO) 31000 [12] standard for risk management. In this way, the SUNRISE Process implicitly builds on concepts, structures and mechanisms that are already existing within CIs as well as regional and national governmental organisations. Accordingly, the SUNRISE Process consists of the five major building blocks "Establishing the Context", "Assessing the Pandemic", "Analysing the Consequences", "Evaluating the Measures" and "Evaluating the Resilience" (see also Fig. 1).

The first block, *Establishing the Context*, sets the scene for the SUNRISE Process and the core aspects for implementing the process are defined. First, this includes the identification of the stakeholders, i.e., the people that are interested in and benefit from the process in general and from its results, in particular. Among them are also the relevant Pandemic-Specific Critical Entities (PSCEs), which are services, infrastructures or people that are mostly affected by the different consequences of a pandemic. As the relation among the PSCEs are of

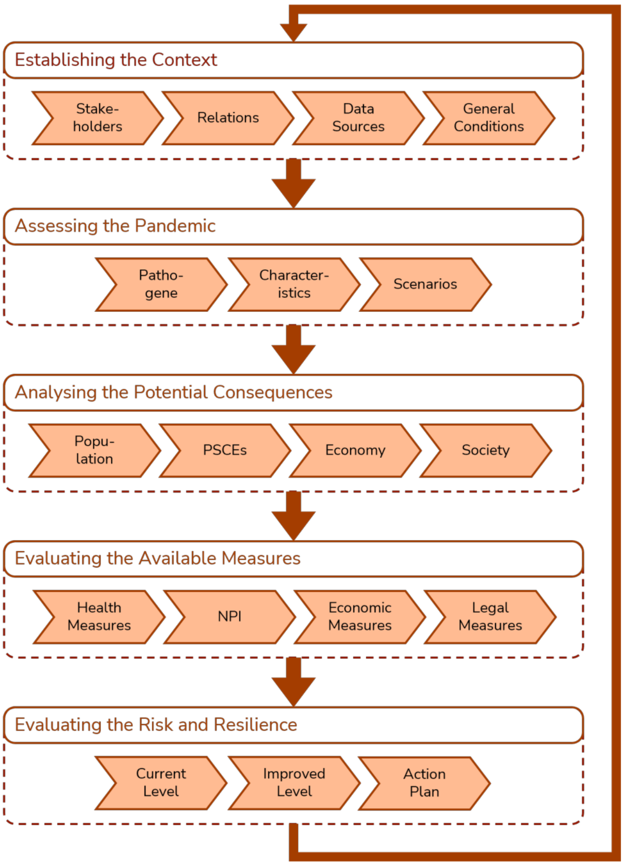

Fig. 1. Illustration of the SUNRISE Process

high interest in the SUNRISE Process, these relations and interdependencies are specifically captured in the next part of the context establishment. These interrelations will also be the basis for analysing the impacts and cascading effects a pandemic can have across different industry sectors and domains of social life. As final steps of this first block, the available data sources and general requirements are identified.

The second block is dedicated to gather information about the main threat, i.e., the pandemic that the CI or the regional or national government is facing. Therefore, the pathogen must be identified in the beginning, which can be done, for example, by using national or international surveillance and monitoring systems. Once it is clear which pathogen is causing the pandemic, more information about its characteristics is required, such as transmissibility, exposure, seriousness of disease, Case Fatality Rate (CFR) and others. These characteristics are essential to obtain a better estimation on the spreading of the pathogen and to decide on possible measure to protect from infection or reduce the spreading. The second block concludes with the definition of potential scenarios that the organisation implementing the process could be facing.

When the scenarios are described in detail, the consequences of the pandemic are analysed in the third block of the SUNRISE Process. Since one major objective of the process is to capture multi-criteria impacts, the consequences are analysed according to four domains, i.e., the effects on the population, on PSCEs, on the economy in general and on the society as a whole. In this way, the process makes sure that the impacts of a pandemic together with the available countermeasures are not only analysed according to the effects on individual and public health but also effects on vital services, economic processes and the societal well-being is captured as well. This multi-criteria approach is of particular importance for governmental organisations on a regional and national level to make sure that they obtain a holistic overview on the impacts of a pandemic and can also identify the best countermeasures not only according to one indicator but to several indicators.

After getting an estimation on the consequences, the fourth block of the SUNRISE Process deals with the identification and evaluation of possible measures to prevent, protect against or mitigate the pandemic. As the SUNRISE Process is focusing on a multi-criteria analysis, also the countermeasures are gathered from different domains: non-pharmaceutical interventions (NPIs) on a personal, environmental and populational level, economic measures and legal measures. The NPIs focus mainly on the health of individual people, i.e., how to protect someone from getting infected with the pathogen or curing their illness, sa well as on reducing the spreading of the pathogen in the general society. Hence, some NPIs such as school closures or lockdowns potentially have huge effects onto the society and implications for the daily life, which need to be taken into account. Since most of the NPIs come with a high cost that cannot be covered by individual organisations, the economic measures describe actions how a state can help in this context, e.g., by providing funds or financial support. All of the measures taken also need to be set within a legal framework as laws and directives are still valid in the course of a pandemic.

The final block of the SUNRISE Process now covers the estimation of the risk level and the resilience level of the services, infrastructures and population in the focus of the analysis. Therefore, the data coming from the consequence analysis is gathered and compiled into one abstract level representing the risk for a given scenario, e.g., a value between 1 and 5 on a semi-quantitative risk scale. The same is done for the resilience level; here, the resilience of individual services and infrastructures is compiled into a resilience level for an entire region or nation. As a second step in this block, the various countermeasures from the previous block are taken into account and a "what-if" analysis is carried out. This analysis assumes that one or several of the measures are implemented and re-calculates the consequences with these measures in place. This will result in a new risk and resilience level, giving the decision makers an estimation, on which set of measures will be most effective according to the criteria from the different domains.

IV. SUNRISE Simulation Tools

The individual steps of the SUNRISE Process can be implemented in different ways, either by literature review and research of existing data sources (e.g., for establishing the context or characterizing the pathogen), by bringing together experts from the various fields and sharing their knowledge in a workshop setting (e.g., for scenario description) or by the application of existing tools for the respective domains. In particular when it comes to analyzing the potential consequences of a pandemic (i.e., Step 3 of the SUNRISE Process, as described in Section III), there are several data sources and specific tools at hand that can support these tasks.

In the following, we will give three indicative examples of tools that facilitate the analysis of the spreading of a pandemic, the resulting economic impacts as well as cascading effects on CIs from various domains and have been extended and adapted in the course of the SUNRISE project. Additionally, there are more tools under development in the SUNRISE project covering other aspects of the analysis of consequences of a pandemic. In particular, four tools are implemented in the project providing specific technical solutions for mitigation activities and the support of NPIs, which are part of Step 4 of the SUNRISE Process. However, a complete description of all these tools would go beyond the scope of this paper.

A. Epidemiological Simulation

The multi-patch epidemiological model is a computational framework used to simulate the spread of infectious diseases in a spatially heterogeneous environment. Unlike simple models that assume homogeneity in population distribution, the multi-patch model acknowledges the spatial heterogeneity in populations, dividing them into multiple interconnected patches or compartments. Each patch represents a distinct geographic area or population subgroup where disease transmission can occur.

The model simulation was originally developed by Rodiah [22], [10] using Python. Parameters, initial conditions, and connectivity matrices can be specified in standard data formats such as Excel, CSV, or custom text files. Simulation results are typically saved as time-series data or visualizations, including graphs and heatmaps. Output formats may include CSV files for data analysis, image files for visualizations. The computational resources required depend on the complexity of the model and the scale of the simulation. Simulations involving many patches or detailed spatial resolution may require significant computational resources, including high-performance computing clusters or cloud-based infrastructure. Memory and processing power are essential considerations, particularly for simulations with a large number of compartments.

At the core of the multi-patch model are differential equations that describe the flow of individuals between patches and the transmission dynamics of the disease within each patch. These equations incorporate parameters such as transmission rates, recovery rates, and movement rates between patches, which are crucial in understanding how the disease spreads across different locations and populations.

One key aspect of the multi-patch model is its ability to capture the effects of spatial connectivity on disease transmission. By considering movement between patches, the model can account for the flow of infected individuals from one location to another, potentially leading to the introduction or amplification of the disease in new areas. This spatial perspective is particularly relevant for diseases with long incubation periods or those transmitted by mobile hosts, such as humans or animals.

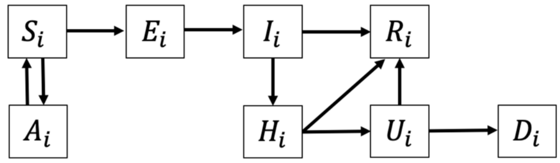

Fig. 2. Illustration of the epidemiological model for direct transmission.

Furthermore, the multi-patch model allows for the exploration of spatial heterogeneity in factors influencing disease transmission, such as population density, contact patterns, and environmental conditions. These variations can have significant impacts on the spread and persistence of infectious diseases, making it essential to consider spatial dynamics in epidemiological modelling and control strategies.

The model is typically set up as a system of differential equations, where each patch is represented by a set of state variables describing the population dynamics within that patch. For the SUNRISE project, each patch within the model corresponds to a Nomenclature of Territorial Units for Statistic Level 1 (NUTS1) subdivision. Within each patch, a meta-population framework is employed to account for the heterogeneity of populations across different CIs. This approach considers various demographic factors, such as age distribution and contact patterns, to capture the nuances of disease transmission within and between subpopulations.

The epidemiological dynamics within each patch are developed by adapting a deterministic Susceptible-Exposed-Infectious-Recovered (SEIR) model, including those transmitted through direct contact or vector-borne transmission. This model distinguishes between healthy (susceptible) individuals, infected but not yet infectious (exposed) individuals, and infectious patients. Moreover, depending on the nature and severity of the disease, it is possible to introduce additional compartments. In the case of severe illness, compartments for hospitalized patients and individuals in intensive care units (ICUs) can be integrated into the model. Subsequently, patients may either recover or die from the disease. Furthermore, an additional compartment is introduced to account for the indirect impact of the epidemic on critical infrastructures, represented as an absence compartment. The model structure within each patch is illustrated in Fig. 2. Therein, an individual in meta-population i is classified either as susceptible (S_i), absence (A_i), exposed (E_i), infectious (I_i), hospitalized (H_i), in intensive care (U_i), recovered (R_i), or dead (D_i).

In scenarios involving vector-borne transmission, the model incorporates additional compartments and parameters to represent the dynamics of the vector population, as well as the transmission dynamics between vectors and humans. This

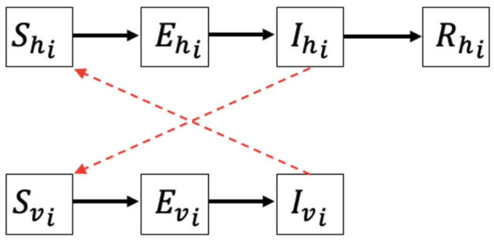

Fig. 3. Illustration of the epidemiological model for vector-borne transmission.

entails introducing compartments for susceptible vectors, exposed vectors, and infectious vectors, alongside parameters governing transmission rates between vectors and humans. The model integrates the interactions between human and vector populations to simulate the spread of the disease in such transmission scenarios. Fig. 3 illustrates the model structure for vector-borne transmission, where a human individual in meta-population i is classified either as susceptible (S_{h_i}), exposed (E_{h_i}), infectious (I_{h_i}), or recovered (R_{h_i}). A vector in meta-population i is classified either as susceptible (S_{v_i}), exposed (E_{v_i}), or infectious (I_{v_i}). Transmission between human and vector represents by red dash line.

B. Cascading Effects Simulation

A Cascading Effects Simulation and Risk Analysis application (in short: CASSANDRA) has been developed in the course of the SUNRISE project, building on and extending already existing approaches of this software. The core of the simulation tool is a NodeJS-based package covering a stochastic simulation of the cascading effects an incident might have on a network of network of assets (which corresponds to a network of interrelated CIs in SUNRISE). Further, the tool has an Angular-based web front-end to support the modelling and to display the simulation results accompanied by a NestJS application providing a REST-API as an endpoint for automated access to the simulation back-end.

The first step in the analysis of cascading effects is to formally describe and model the network of CIs and to create an interdependency graph out of that. In general, this can be broken down into two main parts, i.e., identification of relevant components and identification of the dependencies between these components. The identification of the relevant components depends on the purpose of the analysis. If the focus lies on raising awareness of various existing dependencies, a high-level diagram is sufficient where each CI is represented as one node. If the big picture is known and the focus lies on a deeper understanding, it is required to model a CI in more detail, i.e., represent all its relevant (critical) components as nodes. The granularity depends on the purpose of the analysis, and in some cases also on the availability of data.

When focusing on the effects of an incident, and particularly on cascading effects within a CI network, it is necessary to understand the direction of the propagation of these effects. In the interdependency graph, this is realized by using a directed graph. In the context of the interdependency graph, an edge $X \rightarrow Y$ means that a problem in component X may influence component Y. For example, hospital Y needs drinking water from water utility X.

In general, the dependencies can be of various kinds, and the type of dependency may influence the propagation in the sense that the probability that the problem affects other components may depend on it [15]. An alternative modelling approach classifies the nodes of the networks as physical, cyber, process, human etc. and characterizes the propagation through the node's behaviour [13]. In case of the above mentioned hospital depending on multiple products of the water provider, drinking and cooling water, this dependency is represented as one physical dependency. If this dependency is important, e.g., if the hospital is in the focus of the analysis, a more detailed representation is preferred.

The main purpose of the interdependency graph is to obtain information about the global behaviour of the CI network based on the local behaviour of CIs. These local dynamics are described through a model inside each node, describing how a threat affects this specific node. The first task is therefore to measure this effect. Due to the complexity of the modelled components (either entire CIs or their critical components), it is not feasible to use specific and detailed measures of loss for each node. Instead, a qualitative scale to characterize the state of the node is more favourable, e.g., ranging from 1 (best) to 5 (worst). Depending on the type of the node, the levels represent functionality or availability of a component.

In the context of CIs or their crucial components, data is often sparse or vague, which makes a precise and detailed description of the local dynamics almost impossible. With the choice of a qualitative state, specification of the node's dynamic boils down to describing when it changes its state, i.e., when the condition gets better or worse. Such a change is triggered by an incident, either directly or indirectly through the state of a node it depends on. Further, the reaction to a threat may depend on the circumstances, i.e., on the current state of the node. Such behaviour is best modelled through a Mealy automaton, as it changes its state upon a given input and returns an output. The reaction of a node to an input is influenced in real life by manifold factors that can hardly be captured in full detail in a practical abstract model. Therefore, it is appropriate to model a node's behaviour by adding probabilities to the state changes of the automaton model, i.e., through a probabilistic Mealy automaton [14].

Based on the local dynamics of the individual CIs within the interdependency graph, a simulation approach can be used to describe the global dynamics, i.e., the behaviour of the entire CI network upon a specific incident happening at one of the nodes. This is realized by sending notifications from one node to all its neighbours if a problem has occurred. The Mealy automaton inside each node reacts to an input α and returns an output β if it changes the state (i.e., if it is affected by the trigger). All neighbouring nodes receive this output as new input and may react accordingly. Through this transmission of messages which can be interpreted as alarms, the impact of an incident can propagate through the entire network.

This path of events through all possible dependencies modelled in the interdependency graph describes the potential cascading effects of the threat affecting the initial node. This simulation is carried out by a tool developed by AIT [24], [1], which implements this stochastic process. Because of the probability distributions of the state transitions in the individual nodes, each simulation could lead to a different result. The overall impact of the cascading effects on the entire CI network is then measured by the resulting states of the individual CIs. Hence, the tool runs numerous iterations of the simulation to get a statistical overview on the results.

For the SUNRISE project, to provide a multi-faceted view on cascading pandemic effects, we develop and continuously refine an interdependency graph that can be integrated with both the epidemiological (cf. Section IV-A) and economic (cf. Section IV-C) simulations. To facilitate the integration of the epidemiological simulation, CIs are connected to: i) regional nodes based on their NUTS2 region, and ii) population nodes divided by pandemic-specific age groups (e.g. children, adults, elderly). These connections make it possible to setup transitions for pandemic events like a threshold of the population being admitted to hospitals or ICUs, in turn affecting the operational level of the CIs. In this case, the cascading effects simulation uses simulation data from the epidemiological simulation.

Regarding the integration of the economic simulation, CIs are connected to nodes representing NACE sectors (division of sectors based on [19]). The CIs are connected to specific sectors based on their production and demand of goods and services. These connections make it possible to transfer effects of pandemic events to national NACE sectors, affecting the operational level of economic sectors. In this case, the cascading effects simulation provides input data to the economic simulation in the form of the pandemic-related degrading of operational levels of economic sectors.

C. Economic Impact Simulation

To capture the economic impact of a pandemic, an agent-based model (ABM) has been developed in the course of the SUNRISE project, building on a sector-disaggregated macroeconomic model originally created by Poledna et al. [20]. One crucial aspect in SUNRISE was the required flexibility of the analysis, since the model should be able to potentially cover a wide range of sectors and disasters. The model agents form expectations in each simulation period regarding income, demand, and growth of the Gross Domestic Product (GDP) amongst others based on an autoregressive process of order one. Thus, the agents are not equipped with rational nor model-consistent expectations.

The ABM is implemented as a Matlab simulation and was originally developed by [20] in an open-access manner. Disaster- or model-specific inputs like shocks can be considered in several ways. One possibility is importing personnell numbers, productivity losses or similar through Excel or CSV files.

A complete model computation corresponds to a Monte Carlo simulation of individual model runs. One single model run consists of the iteration through the pre-set timesteps (in quarters), computing all prices, investments, expenditures and others. Random processes are added to the expectations of economic growth and prices, imports, exports, government consumption, and shocks. For each Monte Carlo step, these random elements are newly drawn and the aggregated macroeconomic and disaggregated sectoral indicators computed. For the final results, the variables are summarized over all runs to average out the effects of the random components.

The simulation approach can account for CIs and related capital stocks of sectors based on the statistical classification of economic activities in the European Community, i.e., the NACE level (short for nomenclature statistique des activités économiques dans la Communauté européenne) of the Figaro tables (i.e., Full international and global accounts for research in input-output Analysis) provided by Eurostat. The model is thus based on an input-output framework and originally calibrated for the small open economy of Austria. For the SUNRISE project, the model is being continuously refined and adapted to other national economies and pandemic scenarios. With the given model architecture, data for other European countries can be used for calibration which makes a simulations for those economies possible as well.

The economic impact simulation in SUNRISE considers the following sectors: firms, private households, the general government, banks including the central bank, and the rest of the world. Each sector consists of heterogeneous agents representing either natural persons or legal entities that interact according to predefined rules (see Figure 4). The firm sector is made up of 64 industries, each producing a perfectly substitutable good with labour, capital, and intermediate inputs from other sectors with a fixed-coefficients technology. The model is based on quarterly data and typically runs simulations for up to three years in the current version; this implies a forecasting period of 12 quarters. The model architecture is flexible and allows for several types of simultaneous shocks on a sectoral level. Examples include supply shocks (e.g., due to disruptions in the supply chain), demand shocks (e.g., travel restrictions), changes in productivity (e.g., employees absent from work due to an infection, quarantine or because they need to take care of others) or destruction of capital stock. It is further easy to change parameters to assess the implications and impacts throughout the modelled economy.

The main data source of the ABM is economic data including input output tables, national accounts, capital stocks, business demography, government statistics and population data mainly provided by Eurostat. For the simulation of various pandemic scenarios, additional inputs are required, such as information on the number of persons absent from work (coming from the epidemiological model, cf. Section IV-A, estimated reduction of sectoral output, changes regarding the service level (both coming from the cascading effects simulation, cf. Section IV-B), counter-measures like lock-downs or travel restrictions and others. As an output, the ABM provides

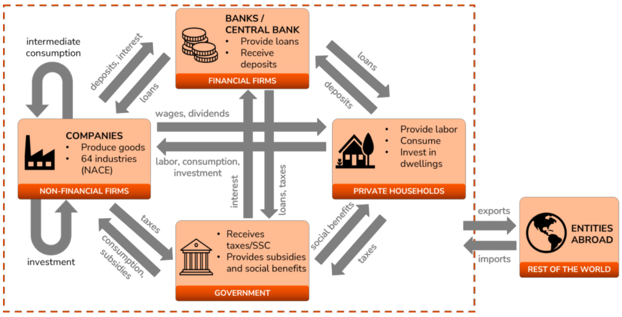

Fig. 4. Illustration of the model agents and their interactions

the standard indicators of a macroeconomic model on which the socio-economic impacts are assessed, e.g., the nominal and real gross value added as well as the employment in each considered sector, the GDP, the total employment as well as the unemployment rate. However, given the model architecture, it is easy to define new economic output variables and have them displayed in addition to the standard macroeconomic outputs.

V. Conclusion

In the face of a pandemic, it is important to support decision makers on a regional and national level as well as CI operators on the selection of the most effective counter measures. However, the COVID-19 pandemic has shown that a sole focus on epidemiological factors is not sufficient in that case but a more holistic view is required that also takes the functionality of the CIs and the socio-economic effects of the respective measures into account. The SUNRISE Process provides such a holistic view by integrating various simulation methods and by evaluating the effects of a pandemic according to multi-domain criteria.

The SUNRISE process as described here is currently given as a first draft and will be further elaborated on in the course of the project. Next steps in the project include a more detailed specification of the process, the integration of additional simulation approaches and the validation of the overall process with CI operators and regional authorities from Italy, Spain and Slovenia.

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