Next Generation Resilience Community-Level Modeling: The Interdependent Networked Community Resilience Modeling Environment (IN-CORE)

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ABSTRACT: In 2015, the U.S National Institute of Standards and Technology (NIST) funded the Center of Excellence for Risk-Based Community Resilience Planning (CoE), a 14 university-based consortium of almost 100 people, including faculty, students, post-doctoral scholars, and NIST researchers. This paper highlights the scientific theory behind the state-of-the-art cloud platform being developed by the CoE - the Interdisciplinary Networked Community Resilience Modeling Environment (IN-CORE). IN-CORE enables researchers to set up complex interdependent models of an entire community consisting of buildings, transportation networks, water and electric power networks, and to include social science data-driven household and business models and computable general equilibrium (CGE) models that predict the level and distributional economic effects of a natural hazard on the community economy. In this paper, an overview of both the IN-CORE technology and the scientific implementation is shown for several of the CoE's testbeds with a focus on four key community stability areas (CSA) that encompass an array of community resilience metrics (CRM). Each testbed within IN-CORE has been developed by a team of engineers, planners, and economists and begins with the initial community description, i.e., buildings and other physical and non-physical models as described above, and progresses to the hazard strike, i.e., a tornado, tsunami, hurricane, or earthquake. This process is accomplished through chaining of algorithms, making the technology modular in nature, which is also explained. Following the initial hazard-induced damage is determined this sets the initial conditions for the recovery models, which are, in a way, the least studied area of community resilience, but arguably one of the most important. Two illustrative examples of community testbeds within the center that look at some combination of population, economics, physical services, and social services are presented.

Keywords: IN-CORE, natural hazards, disasters, risk, uncertainty propagation, decision-support, tornado, tsunami, earthquake, hurricane,

1. INTRODUCTION

Community resilience is the ability of a community to plan for, withstand, and recover from a natural (or other) hazard. Natural hazards worldwide are associated with significant loss of life and direct and indirect losses each year as evidenced by the 2017 U.S. hurricanes Maria and Harvey; past earthquakes, such as the 2010 and 2021 Haiti earthquakes; and the 2010 Japan tsunami. In general, communities understand that resilience is a goal that they strive for, but the ability to systematically improve community resilience has three fundamental requirements: (1) defining resilience goals for the community; (2) understanding and deciding what is being measured within the physical, social, and economic structure of a community; and (3) modeling a community from hazard event through recovery to explore policy options that improve resilience. A comprehensive review of community resilience is available in (Koliou et al. 2018) but significant progress has been made since the time of that review. The science-based multi-disciplinary modeling approaches, quantitative metrics, and data to support such metrics and models for evaluating community resilience are now in a form that can be used by communities and public planners. The computational platform, "Interconnected Networked Community Resilience Modeling Environment" (IN-CORE), can estimate a baseline (current) measure of resilience from which decision-makers can assess how alternative actions will affect community resilience in the models for several dimensions. This paper provides an overview of the science and computational architecture behind IN-CORE across a broad range of natural hazards and scientific disciplines. Two examples are presented to highlight the capabilities of IN-CORE.

2. THE SCIENCE BEHIND IN-CORE

The National Institute of Standards and Technology (NIST)-funded Center for Risk-Based Community Resilience Planning (Center) is implementing measurement science on the IN-CORE platform. It enables decision support through quantitative comparison of alternative strategies for resilience improvement. The IN-CORE output supports decision makers by informing community resilience planning and post-disaster recovery strategies. The modeling environment actively integrates community data with physics-based models of interdependent physical and socio-economic systems to evaluate improvement strategies for resilience. To systematically explain the scientific algorithms implemented in IN-CORE, the conceptual flowchart in Figure 1 is utilized. Figure 1 presents the conceptual structure of IN-CORE, much of which was completed during the first five years of the Center. Significant effort remains to enable a full computational environment for researchers worldwide.

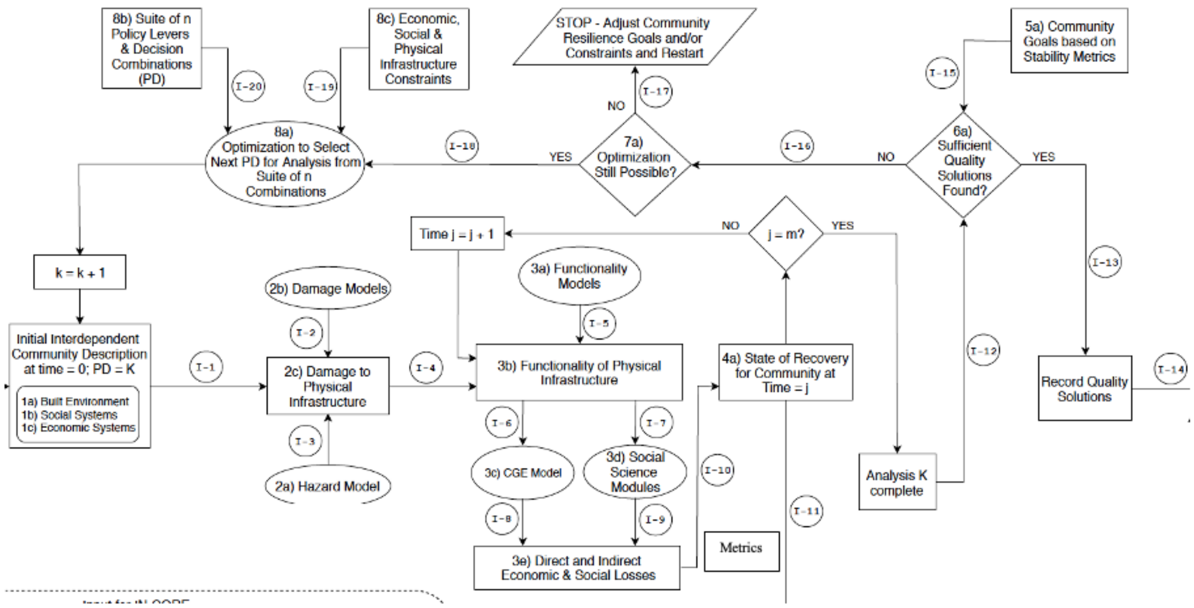

Figure 1: The conceptual structure of IN-CORE (I-11 points to metrics and I-14 points to visualization; both not shown here for brevity)

2.1. INTERDEPENDENT COMMUNITY DESCRIPTION

Moving rightward from the *Start*, the *Interdependent Community Description* consists of three major informational components: (1a) Built Environment; (1b) Social Systems; and (1c) Economic Systems. The Built Environment for a community consists of spatially descriptive data typically using a Geographical Information Systems (GIS) format and includes building footprints and other information needed to assign archetypes for damage and loss modeling; the electrical power network made up of transmission and distribution lines, poles and towers, substations, and power generating plants; the water network consisting of pipelines, treatment facilities, pumps, and towers; the natural gas network including transmission and distribution pipelines, gates, and generating stations; the transportation network, which consists of roadways, bridges, and railways at this stage. Communication networks are included as being co-located with electrical power network transmission towers but have not yet been modeled explicitly. The Social Systems input data to IN-CORE describe households divided into different income groups so that the distributional impacts of a natural disaster can be understood. Social Systems originated from a number of public and other databases. These include U.S. Census block and/or block group socio-demographics; Public Use Microdata Survey (PUMS), which is part of the American Community Survey (ACS) of the U.S. Census Bureau; and Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics (LODES) which provides detailed spatial distributions of workers' employment and residential locations and the relation between the two at the Census Block level. In addition, LODES includes detail on age, earnings, industry distributions, and local workforce indicators, parcel data, and other information from the ACS. These datasets provide a comprehensive description of the social systems governing any municipality. The Economic Systems uses a computable general equilibrium (CGE) model which describes the interaction of households, firms, and the local government in generating economic activity. The construction of the CGE model uses data from the sources presented above. Figure 1 describes the interaction of the built environment, sociological factors and economic activity to generate a holistic approach to examining the impacts of natural hazards.

2.2. DAMAGE TO PHYSICAL INFRASTRUCTURE

The *Damage to Physical Infrastructure* analysis requires all the information described above for the Built Environment to be combined with the (2a) Hazard Model and (2b) Damage Models. The Hazard Model consists of GIS files with the intensity of the hazard defined spatially over the community of interest. There are two types of Hazard Models available for use with IN-CORE. A Tier 1 model is available within IN-CORE for earthquake, hurricane, flood, and tornado, which consists of a researcher-defined set of known parameters that include location, intensity/magnitude, and other hazard-specific parameters. The GIS peak hazard intensity map is then generated for use in the *Damage to Physical infrastructure* analysis. Tier 2 models are also available for the Hazard Models within IN-CORE and include 3D physics-based earthquake rupture/propagation, hydrologic/hydro-dynamic flood, hydraulic tsunami, and coastal storm surge approaches using newly developed and existing software.

2.4 FUNCTIONALITY OF PHYSICAL INFRASTRUCTURE

The *Functionality of Physical Infrastructure* analysis requires input from (3a) Functionality Models, which provides the probability that a building or other Built Environment component is functional due to the level of the damage or state of repair. Functionality indicates whether or not the building can perform its intended function. These models, in the form of functionality fragility functions, are passed to the *Functionality of Physical Infrastructure* analysis through Interface I-6. The functionality of each component within the built environment is then passed to the (3c) *CGE model* and (3d) *Social Science Modules* through Interfaces I-7 and I-8, respectively. Interface I-9 allows communication between the *CGE* and *Social Science Modules* to ensure compatibility of the aggregation levels, databases, and information. The damage to the physical infrastructure as described by the remaining functional commercial and residential buildings is used as input to the CGE model to estimate the economic impact of that natural disaster. The CGE model incorporates information on *Built Environment* functionality as it steps through time, as well as social and economic data from PUMS, LODES, and the U.S. Census data as described earlier. The *Social Science* models consist of business disruption models and population dislocation modules.

2.3. RECOVERY OF THE COMMUNITY

The *State of Recovery for Community at Time = j* represents a point in time and, as such, allows the entire procedure described above to step through time by incrementing index j. However, four areas of *Community Stability Metrics* can be recorded at each time step to document the change over time as the modeled community recovers from the hazard scenario.

2.5 SOLUTIONS AND OPTIMIZATION

To determine if the condition *Sufficient Quality Solutions Found?* has been met, the (5a) *Community Goals based on Stability Metrics* serves as input through Interface I-17. Community goals are specific to each community and are constrained financially and socially during the optimization analysis. Alternatively, a comparison of several policies can be conducted by re-running IN-CORE with modifications to the policies (e.g., a building code revision that would change the community building archetypes and their fragilities).

3. TECHNOLOGY OVERVIEW FOR ALGORITHM IMPLEMENTATION

IN-CORE includes a Service Oriented Architecture (SOA) with RESTful web service technology, lightweight web applications, JupyterHub technology, and the Python computer programming language. On the server cluster, a customized JupyterHub, Python library of scientific analyses, web services, and light-weight web applications are implemented. There are two main parts to the cluster: 1) IN-CORE web services and applications, and 2) IN-CORE Lab. The first part is implemented using a SOA pattern of RESTful microservices, API gateway, and lightweight web applications. The second part uses a JupyterHub to serve a customized JupyterLab with a Python library (called pyIncore), and other common Python libraries (modules). The IN-CORE system utilizes Secure Lightweight Directory Access Protocol (LDAP) at the National Center for Supercomputing Applications (NCSA) at the University of Illinois at Urbana-Champaign for user/group management and authentication. One of the benefits of the platform design is that users can chain together pyIncore algorithms, modify them, and create workflows in a Python script. For example, if a user wants to estimate population dislocation due to a scenario earthquake, they need algorithms for population dislocation and building damage that are able to utilize the data from this scenario. Each algorithm contains a specification with required input (e.g., U.S. Census data) and output data to ensure that the output satisfies the input of the next chained algorithm. For building damage, the user would specify the building dataset, hazard exposure, and fragility curves to compute structural damage. These can be obtained from pyIncore web services. The damage output then feeds into the population dislocation algorithm to estimate the dislocated population. Similarly, users developing new workflows can chain new and existing algorithms to their own model to derive input and output data.

Each service has an access control mechanism by Space (like a workspace), and each user has their own private space that is only accessible by the owner. There are two public Spaces, “incore”, and “ergo”, that anybody who has an account on IN-CORE can access. The “ergo” space contains data from the Ergo/MAEViz repository which was collected by the Mid-American Earthquake (MAE) Center and the Ergo consortium. The “incore” space contains data developed and collected by the CoE and NIST since 2016. The public spaces are managed by the IN-CORE development team at NCSA.

4. DATA STRUCTURE FOR ALGORITHM IMPLEMENTATION

Three web services in IN-CORE manage and serve the data: 1) Hazard service, 2) DFR3 (Damage, Functionality, Repair, Recovery, Restoration) service, and 3) Data service. The hazard service can store and serve datasets with intensity measures (e.g., Peak Ground Acceleration (earthquake), Maximum Inundation Depth (tsunami, flood), EF Rating (tornado)) in geospatial raster (e.g., geotiff) or vector (e.g., ESRI shapefile) format backed by the Data service. The DFR3 service can store and serve various functions related to Damage, Functionality, Repair, Recovery and Restoration. The Data service can store and serve other types of datasets used by IN-CORE.

IN-CORE includes infrastructure inventory data, Census data, economic data, etc. in various formats (e.g., CSV, geotiff, ESRI shapefile, JSON). Note that due to the chaining of analyses, datasets may be connecting across analyses. In other words, an output dataset of one analysis becomes the input dataset of another analysis.

Data in IN-CORE has metadata with specs for hazards, Damage, Functionality, Repair, Recovery, Restoration (DFR3) functions, and datasets. For example, the metadata for fragility functions contain information on demand types and units, function types, and infrastructure types. The metadata for hazards describes the hazard type (e.g., earthquake, tsunami, tornado, flood, hurricane wave/surge, hurricane wind) and supporting demand types (e.g., PGA, Maximum Inundation Depth, Maximum Moment Flux, Maximum Wind Speed). The dataset has general metadata along with dataset type and the name of the schema. Currently IN-CORE has adopted a tabular data specification to express the dataset type schema. The metadata is in JSON format and the semantics service to serve dataset types is in-progress.

5. TESTBED EXAMPLES

5.1. SEASIDE, OREGON TESTBED

IN-CORE was applied to Seaside, Oregon, a small coastal city in the US Pacific Northwest facing the threat from a megathrust earthquake and tsunami on the Cascadia Subduction Zone. Park et al. (2019) quantified the earthquake and tsunami hazards, focusing on five intensity measures for the tsunami: flow depth, speed, momentum flux, arrival time, and duration of flooding.

Subsequently, a multi-hazard damage analysis evaluates the combined impacts of earthquake and tsunami through a stochastic approach that accounts for the accumulated damage due to seismic shaking and subsequent tsunami inundation. The probabilistic seismic tsunami damage analysis (PSTDA) integrates as a step within a resilience-focused risk-informed decision-support system that includes the assessment of direct and indirect socio-economic losses due to tsunamigenic earthquake events. Sanderson et al. (2021) extends this work, considering multiple components of the built environment, including transportation, energy, and water sectors, as well as population characteristics. Damage to all infrastructure systems is evaluated, and the networked infrastructures are used to inform parcel connectivity to critical facilities. The damage, economic loss, risk, and connectivity to critical facilities are apportioned to show economic loss by hazard and infrastructure sector (Figure 2). Kameshwar et al. (2019) developed a framework for community resilience planning under multiple hazards using performance goals established by the community. The performance goals were robustness (e.g., an acceptable level of damage) and rapidity (e.g., an acceptable time to recovery). A key aspect of this framework was that the goals were set as a function of the hazard mean recurrence interval. Results highlight the impact of considering different performance goals, the introduction of ex-ante and ex-post measures, and interdependencies between various infrastructure systems on infrastructure resilience. Park and Cox (2019) present a framework to quantify the amount and location of construction debris generated from and advected with a multi-hazard earthquake and tsunami event, showing how the debris volume increases with increasing mean recurrence interval (MRI) and how the location of the peak cross-shore debris profile is related to the maximum limit of tsunami runup. Kameshwar et al. (2021) used this methodology to quantify the effects of disaster debris, floodwater pooling duration, and bridge damage on immediate post-tsunami connectivity. The results provide insights on immediate post-event connectivity, its evolution with time as floodwaters recede and as the debris is cleared, and the relative effect of debris, floodwater pooling, and infrastructure damage on connectivity.

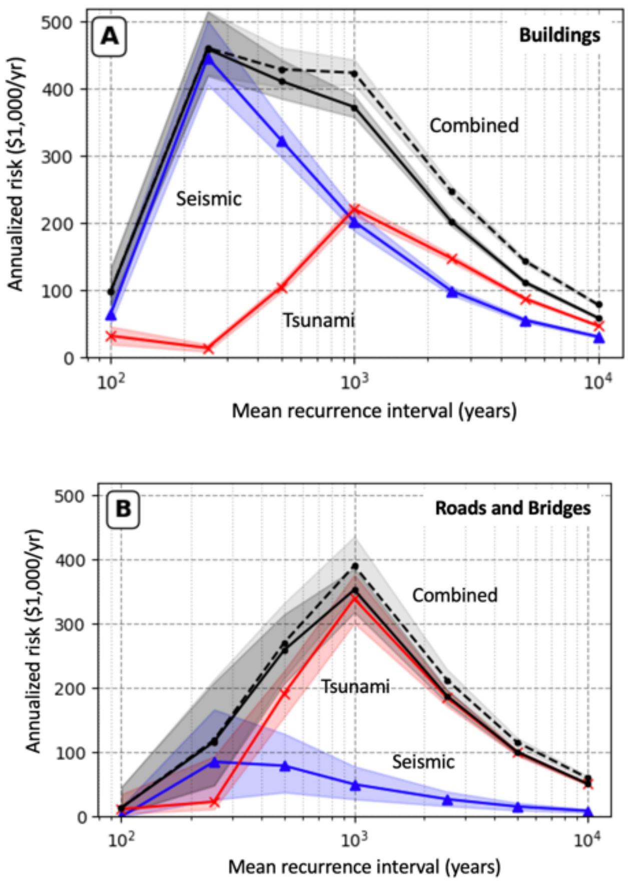

Figure 2: Median economic risks for (a) buildings and (b) transportation network for tsunami (red), seismic (blue), and combined (black) hazards with the 5th and 95th percentiles

5.2. MEMPHIS METROPOLITAN STATISTICAL AREA, TENNESSEE TESTBED

The Memphis Metropolitan Statistical Area (MMSA) could be subject to earthquakes that originate from the New Madrid Seismic Zone and is a Center testbed. The MMSA includes nine counties across three states. The county in the center of the MMSA is Shelby County, which is in the southwest corner of Tennessee, with a population of about 927,644 people. It is the largest and most populated county in Tennessee, encompassing the city of Memphis. MMSA was considered as a testbed because its substantial footprint allows us to 1) demonstrate the scalability of the developed models and solution algorithms to a larger urban area, 2) understand the challenges in performing realistic functionality/recovery analyses (e.g., for the water, power, and traffic flow analyses) at different scales, 3) examine the impact of surrounding community support on urban resilience, 4) integrate the physical damage to buildings with utility disruptions and estimate the post-event functionality loss of building portfolios at the community scale, and 5) model interfaces and information flow between realistic physical, social and economic systems with all their nuances. The MMSA was selected specifically because the MAE Center had completed significant work on Shelby County that can be leveraged (Bai et al. 2014).

To model interdependent infrastructure for a large region, Sharma and Gardoni (2022) developed a mathematical formulation that models infrastructure systems as a set of generalized flow network objects. The formulation introduces dynamic interfaces among the network objects to model infrastructure interdependencies and enables infrastructure-specific multi-fidelity analyses. These interface functions work as correction factors that modify one network's attributes given the values of specific other attributes of the interacting network. Sharma et al. (2020) also developed a mathematical formulation to model the post-disaster recovery of interdependent infrastructure and quantify and optimize their resilience. Specifically, they proposed a multi-scale recovery model that significantly reduces the computational cost of resilience optimization while favoring practical and easily manageable recovery schedules. To quantify resilience, they proposed resilience metrics that capture the temporal and spatial variations of infrastructure recovery. They formulated a multi-objective optimization problem that integrates generalized flow network objects, the multi-scale recovery model, and the resilience metrics to enhance regional resilience while minimizing the recovery cost. The novel optimization algorithm was implemented to improve people's access to water and power in Shelby County following a scenario earthquake from the New Madrid Seismic Zone. Figure 3 shows the improvement in the values of the resilience metric over Shelby County (left) and the distribution of power and water demand (right). Here $Q_\alpha(\tau)$ is the aggregated performance of power and water infrastructure, defined as the product of the power infrastructure performance, $Q_\alpha^{[2]}$ and water infrastructure performance, $Q_\alpha^{[4]}$, at any time τ over an area indexed α, i.e., $Q_\alpha(\tau) = Q_\alpha^{[2]}(\tau)Q_\alpha^{[4]}(\tau)$. Also, $w_\alpha^{[2]}$ and $w_\alpha^{[4]}$ are the demand-based weights of the area indexed α, such that the weight $w_\alpha^{[k]}$ is the ratio of demand in α and total demand for infrastructure k. The resilience measure $\rho[Q_\alpha(\tau)]$ is the temporal center of resilience, which is the centroid of $\mathrm{d}Q_\alpha(\tau)$, the rate of the recovery for $Q_\alpha(\tau)$. The improvement $\Delta\rho[Q_\alpha(\tau)]$ is the reduction in $\rho[Q_\alpha(\tau)]$ over the area indexed α, which can be approximately interpreted as the reduction in time to reach 50% power and water availability. We can see that the optimization improves the resilience metric in the areas with higher demand.

Using this novel computational model for resilience analysis, Tabandeh et al. (2022) developed a formulation to quantify uncertainty in the resilience metrics and find the dominant sources of uncertainty in the resilience analysis. This formulation consists of a multi-level uncertainty propagation approach to reduce the problem dimensionality and a variable-grouping approach to reduce the number of model evaluations. The fundamental idea of the multi-level uncertainty propagation is to break down the high-dimensional problem into several low-dimensional ones and combine their results using a modified chain rule. The variables-grouping approach then provides an adaptive refinement of uncertainty propagation in each of those low-dimensional problems to identify the dominant sources of uncertainty.

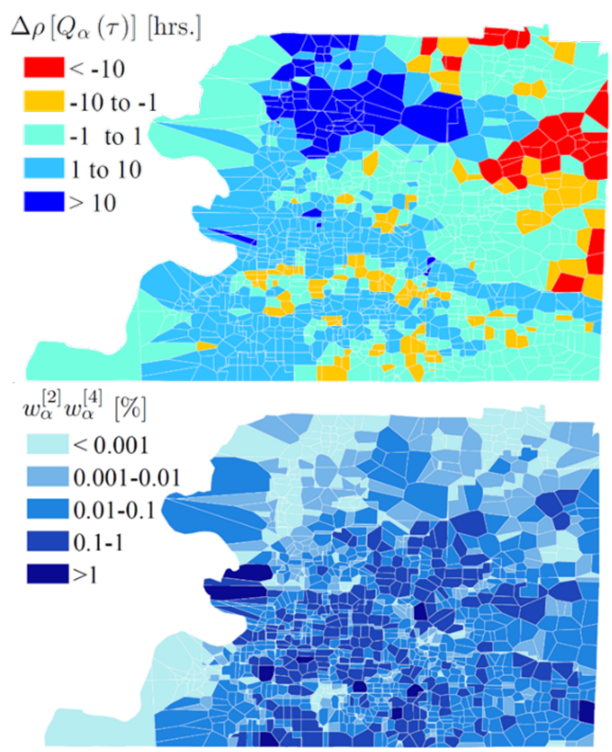

Figure 3: The result of resilience optimization for Shelby County in terms of the proposed resilience metric (upper) considering normalized power and water demand (lower) (Sharma et al. 2020)

6. CONCLUSIONS

This paper highlights the capabilities of the open-source computational platform, IN-CORE, and provides several examples of testbeds. Each testbed was selected on the basis of unique characteristics to accelerate the development of model chaining and interdisciplinary collaboration amongst scientists and engineers. IN-CORE is a computational environment and, therefore, is under continued development and improvement as are all open-source platforms.

However, it is fully usable in its present form for both scientists and communities interested in exploring policy options using “what if” scenarios.

In order to solve a community-level problem such as selection of competing policies, an analyst sets up a model of the community in IN-CORE with the corresponding physical, social, and economic structures in place for each policy, and can chain the analyses to run from hazard event to damage/functionality levels, social and economic impacts, and then recovery of the physical systems as well as social institutions and the economy. Based on a suite of core resilience metrics for IN-CORE, a policy option is evaluated for comparison purposes by the users; this level of system assessment is not available elsewhere. IN-CORE has periodic updates; approximately monthly for minor updates and full version updates every six months.

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