Resilience Aspects in the Sensor Web Infrastructure for Natural Disaster Monitoring and Risk Assessment Based on Earth Observation Data

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***Abstract*—This paper focuses on enabling resilience of the Sensor Web system for disaster monitoring and risk assessment that is based on the use of Earth Observation (EO) data. Resilience is the ability of the system to maintain trustworthy service delivery in spite of changes. Resilience of the EO infrastructure becomes an extremely important issue, especially in the disaster management domain. We propose to enable resilience through: 1) the use of grid resources and services to meet high performance computing requirements; and 2) assessment of resource reputation to select reliable resources. Grid services enable redundancy through integration of heterogeneous resources administrated by geographically distributed organizations. The same services could be provided by different organizations within the infrastructure, and could be of different levels of quality. Therefore, we propose to incorporate a utility-based reputation model to assess reliability of the resources. The proposed approach is implemented within the Namibia Sensor Web Pilot Project that was created as a testbed for evaluating and prototyping key technologies for rapid acquisition and distribution of data products for decision support systems to monitor floods.**

***Index Terms*—Earth Observation (EO), floods, natural disasters, resilience, Sensor Web.**

I. INTRODUCTION

OVER LAST decades, there has been an upward global trend in natural disasters occurrences [1]. Hydrological and meteorological disasters, such as floods and droughts, are the main contributors to this pattern. Disaster management agencies all over the world have to adapt to an increasing number and severity of natural disasters [2], [3]. In recent years, a risk-oriented approach for managing the risks of disasters has been adopted [4]. Risk is a function of two arguments (hazard probability and vulnerability), and represents a mathematical expectation of the vulnerability (consequences) function due to the disasters [4]–[8]. To assess disaster risk, aggregation of heterogeneous data acquired from multiple sources is required [9]–[12].

When disasters strike, rapid and reliable access to data on local conditions, including roads, hospitals, population centers, weather forecasts, and other information can help save lives. Therefore, an operational infrastructure to enable such functionality through, e.g., services is required. Such services would include services for planning and acquiring observations, data processing and products generation, and forecasting and modeling phenomena. The Global Earth Observation System of Systems, or GEOSS, was aimed at strengthening analysis and decision making for disaster response and risk reduction by integrating different types of disaster-related data and information from diverse sources [13], [14].

The Sensor Web approach [15], [16] envisions the coordinated use of Earth Observation (EO) data from both international satellite systems and regional systems [17], [18], and their corresponding geospatial products and services in support of disaster management. Sensor Web provides a set of the standardized Open Geospatial Consortium (OGC) services [19], [20] enabling sensor discovery, planning, and triggering by events, as well as enabling access to and description of observations. In order to enable processing of data acquired by sensors within the Sensor Web, corresponding processing services are required. These services could be provided within, e.g., Grid and Cloud infrastructures [11], [15], [21]–[24]. To provide forecasting capabilities within disaster management domain, corresponding environmental models should be integrated into such infrastructures. Such functionality could be provided within the Model as a Service (MaaS) approach [25] that is applied within the Group on Earth Observation (GEO) Model Web initiative.

The EO systems based on the above-mentioned technologies are dynamic and constantly evolving, and quality of the provided services and datasets might fluctuate with the time. Much attention has been recently paid to providing geospatial data quality indicators and reliability in such EO large-scale service-oriented systems as GEOSS [26], [27]. Therefore, under changing conditions, the system should be able to provided *trusted* and *reliable* services to the users. This property of a system is known as *resilience*. By resilience, we mean *ability to maintain service delivery that can justifiably be trusted in spite of changes in its internal and external contexts or in the interface between these* [28], [29]. Resilience of the EO infrastructure becomes an extremely important issue, especially in the disaster management domain. Users, e.g., local authorities and emergency workers, must be confident that services they utilize can be trusted and are delivered in time with appropriate level of quality.

This paper focuses on enabling resilience of the Sensor Web system for disaster monitoring and risk assessment. In particular, we will focus on delivering trusted and reliable services through the use of Grid resources and services, and assessment of

Manuscript received October 09, 2013; revised January 14, 2014; accepted March 19, 2014. Date of publication August 25, 2014; date of current version November 04, 2014.

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Digital Object Identifier 10.1109/JSTARS.2014.2313573

resource *reputation*. Grid services enable redundancy through integration of heterogeneous resources administrated by geographically distributed organizations. The same service, e.g., flood mapping from satellite imagery, can be provided by different organizations within the infrastructure. These services can be discovered through the GEOSS Component and Service Registry [30]. Resources can provide different levels of Quality of Services (QoS). Moreover, the service might exhibit fluctuations in QoS under changing conditions or system evolution. Therefore, we propose to incorporate a utility-based reputation model [31] to assess trustworthiness and reliability of the resource. Resource reputation is further incorporated into the scheduler to select appropriate services. The proposed approach is implemented within the Namibia Sensor Web Pilot Project that was created as a testbed for evaluating and prototyping key technologies for rapid acquisition and distribution of data products for decision support systems to monitor floods [11].

II. Sensor Web Architecture for Flood Monitoring and Risk Assessment

A. Sensor Web Overview

Sensor Web is an emerging paradigm for integrating heterogeneous satellite and *in situ* sensors and data systems into a common informational infrastructure that produces products on demand (Fig. 1). The basic functionality required from such an infrastructure includes sensor discovery, triggering events by observed or predicted conditions, remote data access, and processing capabilities to generate and deliver data products. Sensor Web is governed by the set of standards, called Sensor Web Enablement (SWE), developed by the OGC [19], [20]. These services include the following.

1) OGC Observations & Measurements (O&M): common terms and definitions for Sensor Web domain.
2) Sensor Model Language (SensorML): XML-based language for describing different kinds of sensors.
3) Sensor Observations Service (SOS): an interface for providing remote access to sensors data.
4) Sensor Planning Service (SPS): an interface for submitting tasks to sensors.
5) SWE Common Data Model: describes data models for exchanging sensor-related data between nodes.

Such infrastructure usually requires computation capabilities to process data acquired by different sensors which can be provided by high-performance computing (HPC), Grid or Cloud services. Senor Web infrastructure should be integrated with the models to enable forecasting capabilities. That can be done, e.g., through services and a Model Web paradigm [25].

B. Sensor Web for Flood Monitoring and Risk Assessment

Flood monitoring and flood risk assessment require the integrated analysis of data from multiple heterogeneous sources such as remote sensing satellites, *in situ* observations, and outputs from models [7], [11], [12], [15], [23]. Flood prediction using meteorological, hydrological, and hydraulic models is adding the complexity of physical simulation to the task [11], [12], [23]. Fig. 2 shows the Sensor Web architecture for flood monitoring and prediction case study [35], [36]. It presents the integrated use of different OGIS specifications for the Sensor Web. The data from multiple sources (numerical models, remote sensing, *in situ* observations) are accessed through the SOS. An aggregator site is running the Sensor Event Service (SES) to notify interested organization about potential flood event using different communication means. The aggregator site is also sending orders to satellite receiving facilities using the SPS to acquire new satellite imagery.

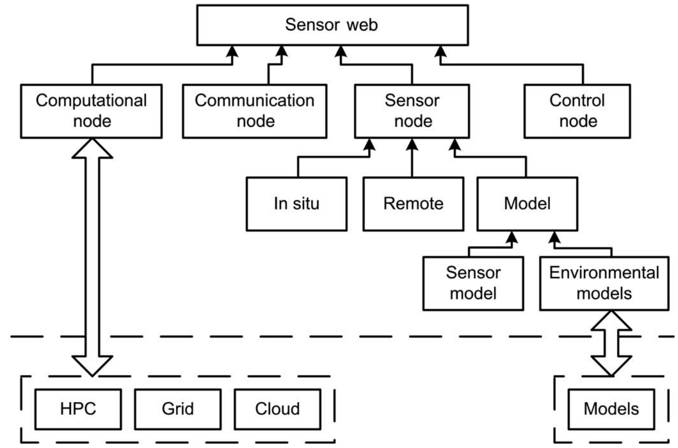

Fig. 1. Components of the Sensor Web and integration with computation capabilities and models through services.

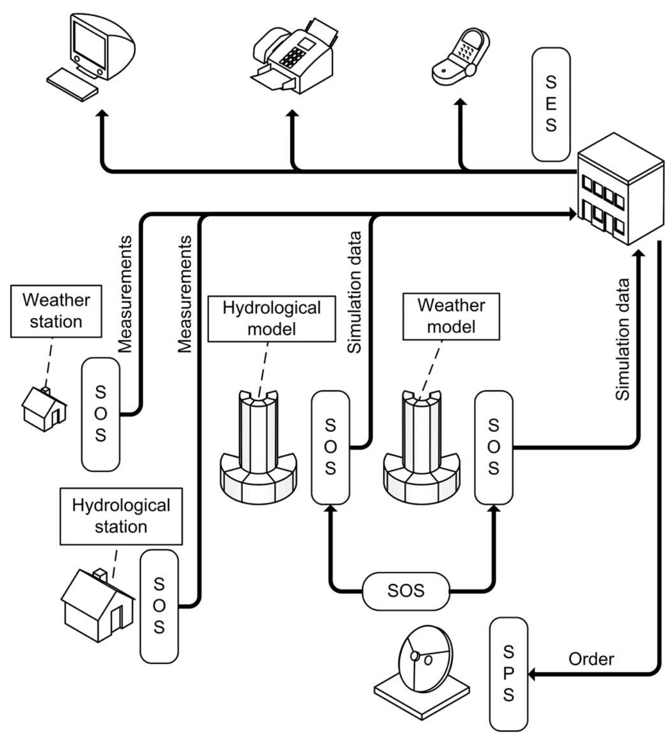

Fig. 2. Sensor Web architecture for flood monitoring and risk assessment.

III. Grid Infrastructure

Grid infrastructure is used to provide computational resources for processing data acquired by the sensors of the Sensor Web, to enable automation and management of the workflow for satellite data processing, and to provide redundancy to ensure resilience.

In order to enable fast acquisition, processing, and delivery of geoinformation products in case of emergency corresponding services were developed within the infrastructure. High-level services include [37]: security subsystem services including reputation management services; data catalog services; metadata services; services for automatic workflow generation; and services for data aggregation, selection, and visualization.

High-level services that require high-performance computations interact with low-level Grid services [37].

1) Grid Security Infrastructure (GSI). To enable security trust between different par-ties in the Grid system, a Public Key Infrastructure (PKI) is traditionally applied. X.509 is the most widely used format which is supported by most of the existing software.
2) Data transfer protocols within Grid (GridFTP). The GridFTP protocol was chosen to provide data transfer between the Grid systems. GridFTP is an extension of the standard File Transfer Protocol (FTP) with the following additional capabilities: integration with the GSI enabling the support of various security mechanisms; improved performance of data transfer by using parallel streams to minimize bottlenecks; multicasting by doing one-source-to-many-destinations transfers.
3) Global Resource Allocation Manager (GRAM). The Grid Resource Allocation and Management (GRAM) service was used to execute jobs on the Grid resources.
4) Credential Management Service (MyProxy). An open-source software MyProxy was used to delegate credentials to services acting on behalf of the users.
5) Replica Location Service (RLS). RLS of the GT is used to provide data replication management in grids. The RLSs provide further abstraction layer for dealing with data by mapping information from logical names for data items to target names.
6) Open Grid Services Architecture—Database Access and Integration (OGSA-DAI) services. This framework provides uniform interfaces to access heterogeneous data.

The use of standardized interfaces and compatible components at the different levels provides scalability and controllability of the system. In particular, a brokering approach [13] is utilized to integrate Sensor Web and Grid services. As the user makes a request for a service for a particular region (e.g., flood mapping service), a request to the SPS is made by the broker for data acquisition. After data are acquired, the broker generates a workflow in a Grid environment. The data from the Sensor Web are provided using the SOS, and, if necessary, large volumes of data (e.g., satellite images) are transferred onto local resources of the Grid using GridFTP. The tasks of the workflow are distributed by the GRAM service onto the working nodes that make calculations. The results provided by different nodes are aggregated and visualized by corresponding services. The results of the data processing are provided via ftp to download the GeoTiff files or coverage WCS, or through mapping services (WMS).

IV. Enabling Resilience in Sensor Web System for Natural Disaster Monitoring and Risk Assessment Based on EO Data

A. Introduction

Service-oriented systems, such as Sensor Webs, are composed of large number of services administrated by different domains. These services differ in design, functionality, and implementation (see Fig. 2). For example, SPS provides application programming interfaces (APIs) for scheduling data acquisitions from *in situ* or remote sensors, SOS provides raw data after acquisition being made, WCS offer the coverage data, etc. What they have in common from user perspective is capability to deliver a specific function(s) with some QoS. At a high level, users are interested in exploiting services that meet their requirements. This leads to the specification of the service level agreement (SLA) between the user and service provider. In the domain of disaster monitoring and risk assessment, the following SLA elements are important: time of products delivery; geospatial resolution and geographical extent of the products; accuracy (e.g., classification accuracy, geolocation precision); types of products; and costs. Service and resource selection can be done at two levels: local scheduling and global scheduling. Global scheduling deals with distribution of user requests between service providers. While local scheduling deals with distributing tasks needed to deliver the particular service among local resources of the service provider. For example, at global level, the user might be offered to select different flood mapping services from satellite imagery. Upon selection of the service, a workflow is generated for data processing and tasks are distributed among resources of the service provider [11], [15], [21], [37].

It should be noted that QoS from different providers might vary, and evolves with the time. In order to select trusted resources and consequently enable resilience, corresponding metrics should be used to quantify the trust. Reputation is one of such metrics. In this paper, reputation is estimated according to the QoS provided by the service provider (see Section IV-B for a detailed description). The main advantage of this approach is that it is high level and quite generic, and does not rely on the specifics of service functionality and implementation. It is especially important for large-scale service-oriented systems such as GEOSS. Therefore, we concentrate on enabling trust and resilience at the level of services.

B. Resource Reputation Assessment in Service-Oriented Systems

We use a utility-based reputation model for estimating resources reputation [31]–[34]. The model is based on the utility function that measures the level of satisfaction of a user in relation to a service provider. In order to define a utility function, an auxiliary function that indicates the SLA accorded between a user and a resource provider is implemented. A penalty function is imposed on a resource provider if the agreed SLA is not met.

In particular, a utility function is defined as [31]

$$U(v_k) = \begin{cases} 1, & \text{if } SLA \text{ met} \\ penalty(\nu_k, SLA), & \text{otherwise} \end{cases} \quad (1)$$

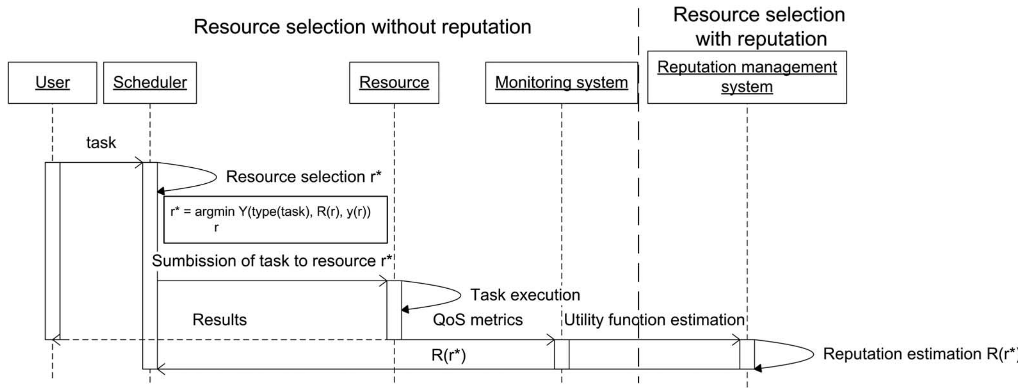

Fig. 3. UML sequence diagram showing resource selection process with reputation.

where SLA is the agreed SLA value between the user and resource provider, ν_k is the obtained value of the QoS metric while delivering service during transaction k, $penalty\,(\nu_k, SLA)$ is a penalty function imposed on a resource provider if the agreed SLA is not met.

In other words, if the service provider respects the agreed SLA, its utility is equal to 1. If the service provider fails to respect the agreed SLA, then its utility will be $U(v_k) < 1$.

The form of a penalty function depends on the QoS in place. For example, for time metrics which usually need to be minimized a penalty function can be represented by

$$penalty(\nu_k, SLA) = \begin{cases} 1, & \text{if } \nu_k \le SLA \\ \frac{SLA}{\nu_k}, & \text{if } \nu_k > SLA. \end{cases} \tag{2}$$

For example, consider the provider that agreed to deliver flood mapping services within 24 h after the request is made (SLA $= 24$). If the provider delivers the service within 12 h then the utility is equal to 1; in case of delivering the service within 30 h, the penalty will be imposed and the utility will be equal to $U(v_k) = penalty(30, 24) = 0.8$.

Reputation is mathematical expectation of the utility function (1) and can be approximated using a sample mean [31]

$$R_r(n) = \frac{1}{n}\sum_{k=1}^{n} U(\nu_k) \tag{3}$$

where $R_r(n)$ is the reputation value of resource provider r at time n.

Therefore, reputation is the expected utility, and is the measure of service reliability in terms of delivering services with the agreed SLA.

C. Service Selection Based on Resource Reputation Value

We used the proposed reputation model for selecting service providers based on resource reputation (Fig. 3). We considered a problem of online scheduling onto resources, and presented a general procedure for integrating reputation into the scheduler using a nonlinear tradeoff scheme [31].

Let R_{r_i} denotes reputation value of resource r_i estimated using (3). When incorporating a reputation into a job scheduler, the following multi-criteria optimization problem arises: we want to minimize the $y(r_i)$ value associated with the scheduler while selecting a service from a resource with maximum reputation R_{r_i}. For this, we utilized a nonlinear tradeoff scheme according to which normalized partial criteria are integrated using the following equation:

$$Y(r_i) = \frac{\alpha_1}{1 - y_n(r_i)} + \frac{\alpha_2}{R_{r_i}} \tag{4}$$

where α_k are parameters and $y_n(r_i)$ is the normalized value of the criterion associated with the scheduler.

The service is assigned from the resource which minimizes the value given in (4), i.e.,

$$r^* = \arg\min_{r_i} Y(r_i). \tag{5}$$

The advantage of using such a scheme is that it provides a Pareto-optimal solution partially satisfying criteria with corresponding weights. The experiments showed that the scheduler with knowledge of reputation using a nonlinear tradeoff scheme outperformed a scheduler without knowledge of reputation on average 45% for all performance metrics used in the study [31]: makespan, average task execution time, average task queue waiting time, average task access time, number of times SLA was not met, average utility, and resource utilization.

D. Incorporation of Reputation into Service-Oriented Systems

The proposed model is incorporated into the service-oriented system architecture to enable resilience. The generic architecture is shown in Fig. 4. The functionality of the main components is as follows.

1) *Users* exploit services. The user can be a human being that gets access to services through, e.g., a geoportal or a system that get access through APIs.
2) *Resource* provides services to the users.
3) *Virtual organization (VO)* is a set of individuals and/or institutions defined by coordinated resource sharing rules for reaching common goals.
4) *VOMS* is the Virtual Organization Management Server.
5) *Service* is a specified functionality delivered by a resource provider or a component.
6) *Service catalog* contains metadata on the registered services.

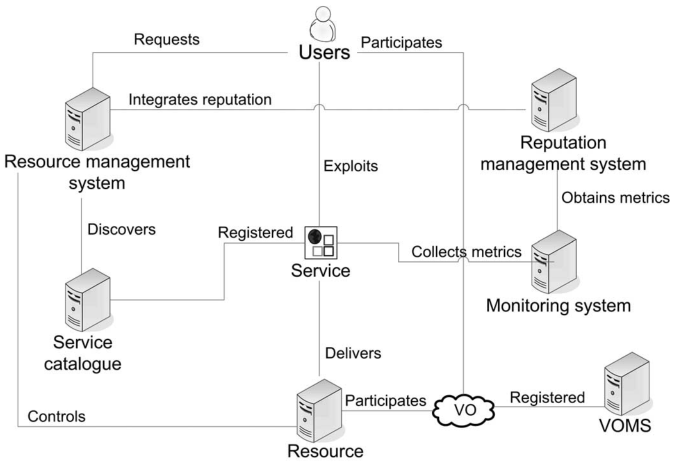

Fig. 4. Integration of reputation components that enable resilience into service-oriented systems.

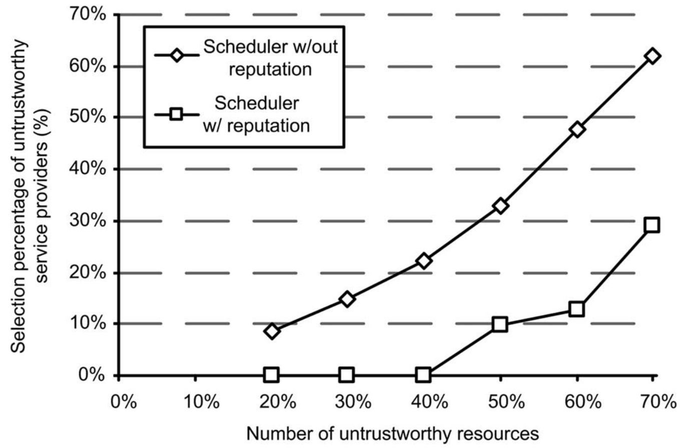

Fig. 5. Selection percentage of untrustworthy service providers depending on the number of untrustworthy resources.

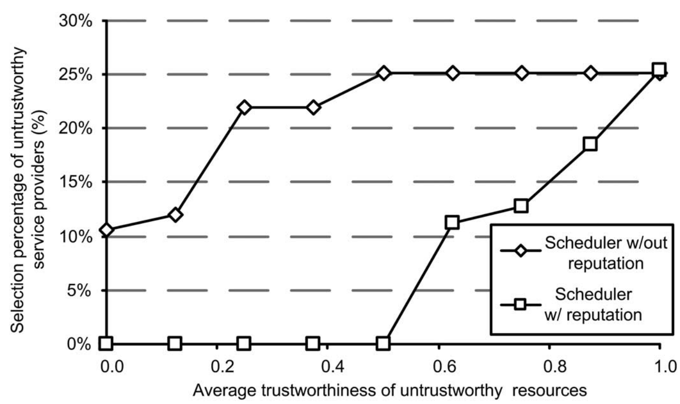

Fig. 6. Selection percentage of untrustworthy service providers depending on resource trustworthiness rate.

7) *Resource management system* (broker) processes requests from users, discovers services that meet user requirements in the catalog, and selects appropriate services according to (5). Resource reputation is obtained from *Reputation management system*.
8) *Reputation management system* implements the proposed approach and estimates and updates reputation of resources. It interacts with the *Monitoring system* to obtain QoS metrics for estimating the utility function and consequently reputation.
9) *Monitoring system* collects data on service performance metrics (in particular, QoS and SLA).

V. Performance Analysis

This section provides results of experiments to validate the proposed approach. First, we describe experiments on simulated data and then real data.

A. Enabling Resilience Through Reputation Model

Resilience is ability of the system to maintain trustworthy service delivery in spite of changes. These changes can be of different nature [29], e.g., variations in system workload or number of reliable resources. An important property of the developed scheduler is that it maximizes selection and utilization of trustworthy (reliable) service providers when the number of untrustworthy (unreliable) resources is high. We run two sets of experiments to assess efficiency of using the utility-based reputation model for enabling resilience in the Sensor Web. All experiments were run for a Sensor Web system with 20 service providers. The request arrival rate was modeled from real systems, while other parameters such as SLA, QoS, and service capacity were simulated. Since in our simulations random values are generated, it is important to analyze performance for multiple simulation runs to be able to generalize obtained simulation results. In order to accomplish this, simulations were run for different seed values to generate random values. The obtained values for multiple runs were averaged across multiple runs.

Within the first set of experiments, we varied a number of untrustworthy service providers that always provide bad services. Here, by “good” (trustworthy) and “bad” (untrustworthy) services, we mean situations when a resource provider respects the agreed SLA, and when the agreed SLA is violated by a resource provider, respectively. Fig. 5 shows the selection percentage of untrustworthy service providers (SPUSP) depending on the number of untrustworthy resources. The SPUSP value was below 15%, when the number of untrustworthy resources was 60%, and was below 30%, in case of 70% of untrustworthy resources. The proposed scheduler started to select services from untrustworthy resources only when the number of untrustworthy resources was 50% of the total number of resources in the system.

Within the second set of experiments, we varied the resource trustworthiness rate for the untrustworthy resource providers. If resource trustworthiness rate is equal to 0.6, then it meets the agreed SLA on average in 60% of cases. We allowed 20% of the resources to be untrustworthy but with different degrees of trustworthiness. When using the proposed scheduler, no services were selected until resource reputation became high, in our cases until average resource trustworthiness rate was more than 0.5 (Fig. 6). When untrustworthy resources became reliable (average trustworthiness rate was equal 1), then both schedulers selected about 25% of these resources.

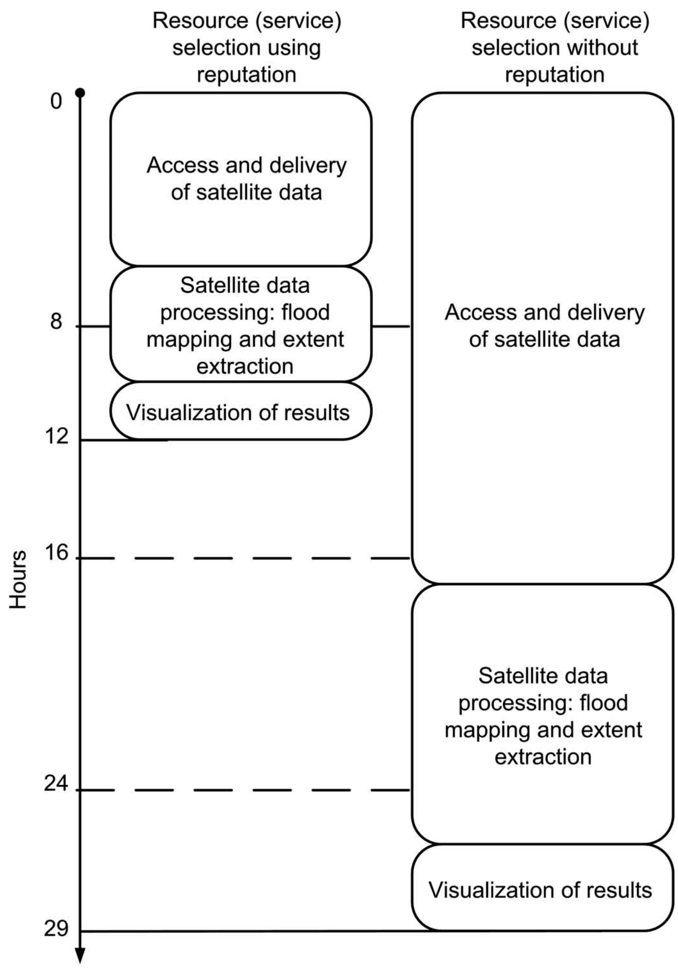

Fig. 7. Resource selection (with and without reputation) for the flood mapping service.

Therefore, utilization of resource reputation for selecting services allows us to exclude or limit the use of unreliable and untrustworthy service providers in the heterogeneous infrastructure. Under changing conditions (system workload, number of unreliable resources), the system is able to maintain delivery of reliable services that conform to the agreed SLA with the users, thus enable resilience of the whole system.

B. Case Study: Namibia Sensor Web Pilot Project

The approach described in the Section IV is being implemented within the Namibia Sensor Web Pilot Project [11]. The project was created as a testbed for evaluating and prototyping key technologies for rapid acquisition and distribution of data products for decision support systems to monitor floods and enable flood risk assessment. One of services currently available through the Sensor Web infrastructure is a flood mapping service provided by Space Research Institute NAS Ukraine and SSA Ukraine (SRI). The service provides flood extent maps derived from synthetic-aperture radar instruments onboard Envisat/ASAR and Radarsat-2 satellites [39]–[41]. The maps are provided on demand and delivered within 12 h after image acquisition. The services are run within the Grid infrastructure developed at SRI. Fig. 7 shows the influence of using reputation for services selection within satellite data processing for rapid flood mapping. The use of reputation allowed us to select reliable services that reduced the overall time required for delivering flood services to the end users.

VI. Conclusion

In this paper, we focused on enabling resilience of the Sensor Web system for disaster monitoring and risk assessment through the use of Grid resources and services, and assessment of resource reputation. Resilience of the EO infrastructure becomes an extremely important issue, especially in the disaster management domain. Users utilizing EO services must be confident that services they utilize can be trusted and are delivered in time with appropriate level of quality.

Resilience is enabled through the use of Grid services that provide redundancy through integration of heterogeneous resources administrated by geographically distributed organizations. The same services could be provided by different organizations within the infrastructure, and could be of different level of quality. Therefore, we incorporated a utility-based reputation model to assess reliability of the resources. Reputation is further integrated into the scheduler that selects service providers. The use of scheduler with reputation allowed us to exclude or limit the use of unreliable and untrustworthy service providers. In particular, results of simulations showed that selection percentage of untrustworthy service providers was below 15% when the number of untrustworthy resources in the system was 60%, and was below 30%, in case of 70% of untrustworthy resources. Also, when varying the resource trustworthiness rate, the proposed scheduler did not select a service provider when its reputation became 0.5. The proposed approach was tested within the Namibia Sensor Web Pilot Project. With enabled computational and storage services provided by Grid infrastructure and reputation-based service selection, it was possible to generate flood maps within 12 h after data acquisition.

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