Identification of the energy system critical elements using the PARMONC library

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Abstract. In this paper, we presented a Monte Carlo-based approach for vulnerability analyse of energy systems. For high-performance Monte Carlo simulation the PARMONC software library was used. The PARMONC is implemented on high-performance clusters of the Siberian Supercomputer Center. The PARMONC effectively launches parallel stochastic simulation on supercomputers with different architectures. The proposed approach was applied for the identification and ranking the most important elements of a real-world natural gas supply system.

1. Introduction
Modern infrastructures are complex, large-scale, man-made systems that function interdependently to manufacture and deal out essential goods and services [1]. An infrastructure is regarded as critical if its malfunction or destruction has a serious impact on the health, safety, security, economics and social well-being.

An energy system is one of the key critical infrastructures [1]. Energy systems could suffer from many types of disturbances. The disturbances are random failures, natural hazards, and intentional attacks [2].

Random failures can touch all almost identical components of an infrastructure with the same probability distribution [3]. The position of a component has no influence on the probability of failure.

Natural hazards include earthquakes, hurricanes, and lightning [4]. In opposite to random failures, the geographic position affects the probability of failure of a component.

Intentional attacks can be divided into pointwise and proximity-based [5, 6]. Pointwise attack scenarios do not depend on the geographical location of the components. The proximity-based attacks choose a set of local nodes, edges, or paths to strike. As an intentional attack targets the specific elements, the probability of failure and randomness are not implied.

The resilience is the ability of a system to adapt to disturbance scenarios and recover to pre-disaster states [7]. A conceptual resilience evaluation framework consists of four stages: disturbance characterization, vulnerability analysis, system reaction or operation and system's restoration [8].

Vulnerability is a widely used concept and is often defined as a system’s overall susceptibility to a specific hazardous event [9]. In other words, it represents the magnitude of the system damage given the occurrence of that event.

There are three perspectives of the vulnerability analysis which are closely related with the types of disturbances [10]. First, a global vulnerability analysis perspective is taken where disturbances of...
increasing magnitude are applied to a system and consequences of the disturbances are evaluated [11]. The second is a systematic identification of critical components or sets of components. The criticality of a component or set of components is considered to be the vulnerability of a system to failures in these components. The more vulnerable the system is to the failure of a specific component or set of components, the more critical are the component/components [9]. Thirdly, a systematic identification of critical geographic locations is carried out by deleting components that are spatially proximate to each other and evaluating the consequences [5, 6].

Two techniques frequently used in energy system vulnerability analysis are Monte Carlo simulations [12] and contingency analysis.

Contingency analysis is performed according to N-1,...,N-k security criteria, where N and k=1,...,N refer to the total number of components and the number of simultaneous or near-simultaneous component failures, respectively [13, 14]. A distributed computing environment supporting energy system N-k contingency analysis presented in [15] is shown in the Figure 1. It includes information and computation resources, their software and hardware, applied software that implemented models of energy systems and models for decision-making support, computing and geo-information services, expert tools, various databases, and data converters. Within the environment, the complex challenge of integration, configuring, and rational use of the above-listed components is solved. Its effective solution is provided through applying advanced tools of supercomputer engineering and multi-agents technologies [16].

Figure 1. The scheme of the environment to support N-k contingency analysis.

There are two main approaches to Monte Carlo simulations: state sampling and sequential sampling. In state sampling, the system states are randomly sampled based on an estimated distribution of failures; in sequential sampling [17], the chronological behavior of the system is simulated by considering component state transition probabilities.

The vulnerability analysis is not an easy task, given the structural and dynamic complexities of the systems and processes: a big, combinatorial set of possible scenarios, events and conditions has to be evaluated. It makes experimentation economically uncertain and physically impracticable. However, it is the continuous achievements in modeling techniques and growing economical availability of high-performance computing systems that greatly simplify the use of simulation for capturing particular system behavior details for vulnerability analysis [18].

In this paper we present a probabilistic approach for identification and ranking of critical components of an energy system implemented on top of a library that can effectively parallelize the Monte Carlo simulation.

The paper is structured as follows. Next section provides a shot review of related works. A Monte Carlo simulation library PARMONC is described in Section 3. A methodology is considered in Section 4. The results of computational experiment are discussed in Section 5. Finally, Section 6 summarizes the results of experiment.
2. Related work
A Monte Carlo simulation-based approach has been developed in [19] to analyze disturbances in the natural gas transmission network. The vulnerability identification algorithm is used for finding critical component which failures lead to the most significant supply disruptions. A stochastic flow network model developed in [19] is used in the multi-perspective framework of vulnerability analysis [19]. The framework allows identifying the importance of critical infrastructure elements and quantifying the failures consequences with respect to supply service, controllability and topology.

Monte Carlo simulations have been generally accepted as a standard in system reliability analysis [18]. For example, they are widely used for natural gas supply systems [19, 21, 22] and power systems [17, 23, 24]. Reliability analysis focuses on the system likely behaviour in terms of indices describing characteristics such as the frequency of failures and the average duration and magnitude of these failures. Disturbances with low probability/frequency of occurrence have a rather small impact on the reliability indices. However, as many of those may lead to large-scale consequences, such disturbances are the major focus of and captured by the vulnerability analysis [25].

To increase the efficiency of Monte Carlo simulations, some modifications have recently been proposed in the literature [13], such as artificial neural network [26], hybrid fuzzy Monte Carlo technique [27], Latin hypercube sampling [28]. Also variance reduction techniques, such as the important sampling [17] and antithetic variates method [29], may be used to manipulate the way each sample of a Monte Carlo simulation is defined in order to both preserve the randomness of the method and decrease the variance of the estimation [30].

In parallel Monte Carlo simulations, it is very important to ensure the low relevance of the random numbers generated among the processors, to achieve high accuracy of the results [31]. This can be achieved by utilizing a special Monte Carlo simulation library like PARMONC [32].

3. PARMONC library
For effective parallelization of the Monte Carlo simulation we use the PARMONC [32] - the library of easy-to-use programs that was implemented on high-performance clusters of the Siberian Supercomputer Center and can also be used in other supercomputer centers. The description of the PARMONC can be found on the web site of the Siberian Supercomputer Center.

The main features of the PARMONC are as follows:
- it is suitable for the massively parallel stochastic simulation for a wide range of applications,
- it is a software framework to parallelize stochastic simulation to be applied without knowledge of MPI language.

The PARMONC effectively launches stochastic simulation on supercomputers with different architectures. Also, it is scalable from current supercomputers to more powerful ones up to future exaflop supercomputers.

The following features distinguish the PARMONC from other software tools and make it an easy-to-use instrument for specialists in the field of stochastic simulation:
- The only thing the user has to do in order to parallelize stochastic simulation is to write in C, C++ or in FORTRAN a sequential subroutine to simulate a single realization of a random object of interest and to pass its name to the PARMONC routines.
- In his/her sequential code, he/she uses a PARMONC function, which implements a parallel RNG, in a usual and convenient way.
- In the course of simulation, the PARMONC periodically calculates and saves in files the subtotal results of simulation and the corresponding computation errors.
- The PARMONC provides an easy-to-use technique to resume stochastic simulation after its termination with automatic averaging of the results of the previous simulation.

4. Methodology
An energy system network is represented as a graph $G = (N, E)$, where $N$ is a set of nodes, $E \subseteq \{(i, j) : i, j \in N, i \neq j\}$ is a set of arcs, the arc $(i, j) \in E$ represents energy transport, $i$ and $j$ are the starting and ending nodes of the arc $(i, j)$, respectively. The flow over the arc $(i, j) \in E$ and its capacity (the maximal flow) are denoted by $y_j$ and $b_j$, respectively. We consider the minimum cost
flow problem that is related to determining the maximum flow $Z_{st}$ with lowest cost between a common source (node with the index $s$) and sink (node with the index $t$). This problem is formulated as follows \cite{33}:

$$\sum_{(i,j) \in E} k_{ij} y_{ij} \rightarrow \min,$$  \hspace{1cm} (1)

$$\sum_{i \in N_j} y_{ij} - \sum_{i \in N_j} y_{ji} = \begin{cases} -z_{st}, & \text{if } j = s, \\ z_{st}, & \text{if } j = t, \\ 0 & \text{otherwise}, \end{cases}$$  \hspace{1cm} (2)

$$0 \leq y_{ij} \leq b_{ij},$$  \hspace{1cm} (3)

where $k_{ij}$ is the flow cost over $(i,j) \in E$, $N_j^i$ is the subset of input arcs for node $j$, $N_j^j$ is the subset of output arcs of node $j$. Equation (2) ensures that the input flow and output flow for any node will be equal. The flow constraints in equation (3) ensure that the flow over any arc will be non-negative and will not exceed its capacity.

The problem (1)-(3) is the simplest energy system model to evaluate the system performance degradation under a disturbance impact. It underlies a task of identifying and ranking critical components and sets of components.

A disturbance scenario is the attack on a network element. The remaining network components can fail according to their specific probabilistic model. Then we calculate the flow over the energy system according the problem (1)-(3) and evaluate the disturbance on the end consumers. More generally, a computational experiment consists in generating by means of PARMONC a large number of samples of system response on the attack and components failure and counting the total energy resource shortage. The higher is the shortage the more critical is the element under attack.

5. Experimental analysis

Within this experiment, we determine critical components of the Unified Gas Supply System of Russia. The system network consists of the 382 nodes, including 28 natural gas sources, 64 natural gas consumers, 24 underground natural gas storages, and 266 compressor nodes. In addition, it includes 486 arcs representing main natural gas pipelines and branches to distribution networks. Figure 2 represents the topology of this network. Some the most critical elements found with help of PARMONC are shown in the Table 1. The values in the second column of the Table 1 are particular shortages related to the total natural gas demand.

![Figure 2. The topology of the Unified Gas Supply System of Russia.](image)
### Table 1. The most critical elements of the Unified Gas Supply System of Russia.

| Anonymized element | Total shortage, % |
|--------------------|-------------------|
| Arc A-B            | 29.6              |
| Node A             | 29.5              |
| Arc B-C            | 29.2              |
| Node B             | 29.1              |
| Node D             | 28.5              |
| Node C             | 28.4              |
| Node E             | 28.2              |
| Arc D-C            | 28.1              |

### 6. Conclusions

In this paper, we presented a Monte Carlo-based approach for vulnerability analyses. The approach provides an indication of the worst networks elements in terms of security of supply and provides their numerical ranking. The proposed Monte-Carlo-based approach was applied for the identification and ranking the most important elements of a real-world natural gas supply system.

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