An Open-Source Toolbox for investigating functional resilience in sewer networks based on global resilience analysis

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Abstract

Resilience analysis of urban infrastructures such as sewerage systems is very important due to different stressors. Failure in these infrastructures may lead to economic, social, health and environmental consequences. The functional resilience of systems can be analyzed in all failure levels caused by unpredictable or even unknown events based on the global resilience analysis (GRA) method. To perform GRA under different scenarios of pipe collapse and blockage, the performance of the system must be evaluated in all possible link failure combinations. The time of this process might be unfeasibly long in real sewerage networks. In this paper, an open-source toolbox is developed which uses a proposed scenario selection method based on roulette wheel to perform GRA without simulating all possible scenarios. This toolbox is based on a proposed O-SWMM API which is a developed version of EPA's Storm Water Management Model (SWMM) to optimize simulation time and memory usage. The results show that the mean resilience for a sample and also a real sewer network was estimated by the proposed method with RMSE less than 0.025 and 0.022 respectively comparing with simulating all possible scenarios. Moreover, the GRA computation using O-SWMM API was at least 2.26 times faster than SWMM.exe.

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1. Introduction

Many infrastructure systems such as sewer networks must be investigated in exceptional conditions. Because, failure of these systems can lead to serious economic, social, environmental, and health consequence (Davis et al. 2013). The origin of the word resilience is the Latin word "resiliere", which means to "bounce back" (Hosseini et al. 2016). Doorn et al. (2019) used a formal concept for the resilience. They defined performance of resilience as the ability to keep or enhance certain functions. This concept was used by Chen et al. (2021) to develop a methodology for quantifying the resilience of hazardous storage systems. Mottahedi et al, (2021) suggested the definition of "the ability of a critical infrastructure system exposed to hazards to resist, absorb, accommodate to and recover from the effects of a hazard in a timely and efficient manner, for the preservation and restoration of essential services" for evaluating resilience. Cai et al. (2021) defined the resilience as the ability of systems to recover quickly after external disruptive events.

In this paper the definition of resilience in Butler et al. (2014) is used. They defined resilience as "the degree to which the system minimizes level of service failure magnitude and duration over its design life when subject to exceptional conditions".

Risk analysis is commonly summarized as incorporating both the probability of an event and the consequences (Johnson et al. 2021). However, various events threaten sewer networks which some of them are unknown or unpredictable and the probability of their occurrences cannot be determined (Sweetapple et al. 2018). Moreover, each event might have several different consequences or different events can lead to the same end states (Johansson et al. 2011). Therefore, this paper focused on a middle state analysis.

The middle state analysis method evaluates the system performance based on consequences caused by different and unknown threats and emphasizes on response of the level of service provision to system failure. It is more easily identifiable and measurable than identification and analysis of multiple threats. In the middle state analysis, the consequences of the events that result in the same system failure mode can be addressed with a single analysis regardless of their type to represent all the potential modes of failure. Therefore, it enables a more comprehensive resilience assessment and improves the adaptation development process (Butler et al. 2016).

Johansson et al. (2011) presented a method for the global vulnerability analysis (GVA) of technical infrastructures and used it for an empirical analysis of the electrical distribution systems. Mugume et al. (2015) introduced global resilience analysis (GRA) in urban drainage network based on the middle state approach. The GRA investigates the network at all different failure levels (number of failed links) from zero to 100 percent in order to analyze resilience of network in different level of consequences. This method has four steps. Firstly, the failure mode (i.e., sewer collapse or blockage) needs to be identified. In the second step, the system stress (percentage of failed components i.e., earthquake, oil clogging) associated with the failure mode and the simulation manner are identified. Then, the system corresponding strain (resulting loss of system functionality) is detected and determined how to measure it. And finally, the failure mode strains are simulated under increasing stress magnitude up to 100 percent of maximum stress (Mugume et al. 2015).

Sweetapple et al. (2018) presented a GRA toolbox for water distribution systems based on EPANET software application, but there is no toolbox for analyzing global resilience in sewer networks. In sewer networks, conduit blockages due to accumulation of sediment, fat, oil, and grease, or tree root penetration, can cause the sewage to be overflow in residential areas (Davis et al. 2013). Although, these threats are related to operations and management, the critical blockages due to some threats such as earthquakes and floods can cause blockage in a large number of links in the sewer networks (Hughes et al. 2020). This number can be much more than 5 to 10 percent, especially in earthquake-prone countries such as Iran (Kamranzad et al. 2020). Heavy storms in combined networks can also cause similar consequences. These events are not generally predictable and thus, the consequences of all possible scenarios must be investigated. Such analysis is computationally expensive and quickly becomes complex for even small systems (Johnson et al. 2021). Therefore, in sewer networks with large number of conduits and manholes, simulation of all possible scenarios (GRA) is unaffordable in some circumstances.

Mugume et al. (2015) used the sequential random link selections method for sewer networks in order to overcome GRA’s computational challenges. Diao et al. (2016) proposed a semi random selection method for GRA and applied it to water distribution systems. In their method, at each stress magnitude a fixed number of failure scenarios are generated randomly and $2\lfloor c-(c_f-1)\rfloor$ number of failure scenarios are generated in a targeted manner, where c and c_f are total and failed components, respectively. Atashi et al (2020) also used the same selection method as Diao et al. (2016) to determine the total number of scenarios in order to evaluate the resilience of water distribution systems based on location of isolation valves. In Diao et al. (2016), the total number of scenarios is directly related to the number of links in the network but Mugume et al. (2015) used a convergence analysis method to determine the required number of scenarios. Therefore, this number is different for each sewer network and is based on the characteristics of that network.

Although, this approach is used to specify sufficient number of random selections, but improving the selection method can generate results that are closer to the resilience computed using all possible scenarios. Finding the scenarios generating lowest and highest resilience in each failure level can lead to achieving this goal.

In this study, a toolbox is presented for GRA in sewer networks which make a trade-off between time and reliability of results using a proposed multi criteria selection method based on roulette wheel. This method finds the scenarios with lowest and highest resilience in each failure level named as strategical scenarios and uses them to generate the scenarios of the next failure levels. The toolbox is able to simulate the selected scenarios based on a development of the SWMM engine to reduce simulation time of each scenario.

2. Parallel GRA toolbox

In this study, an open-source toolbox is proposed in C# language for analyzing global resilience of complex sewer networks[2]. This toolbox simulates the sewer systems using a developed engine which is based on SWMM (Storm Water Management Model).

The toolbox consists of three main blocks (Fig.1): scenario generator, parallel O-SWMM simulator and GRA engine. The scenarios generator block generates the compendious set of scenarios using a proposed multi criteria selection method based on roulette wheel. The generated scenarios at each failure level are simulated via parallel O-SWMM block, which contains several simulation engines (called simulator). Finally, the global resilience of sewer networks is determined by GRA engine block. These blocks are more described in the following sub-sections.

[2] Availability: https://github.com/BehnazKamali/OSWMM-GRA-Toolbox

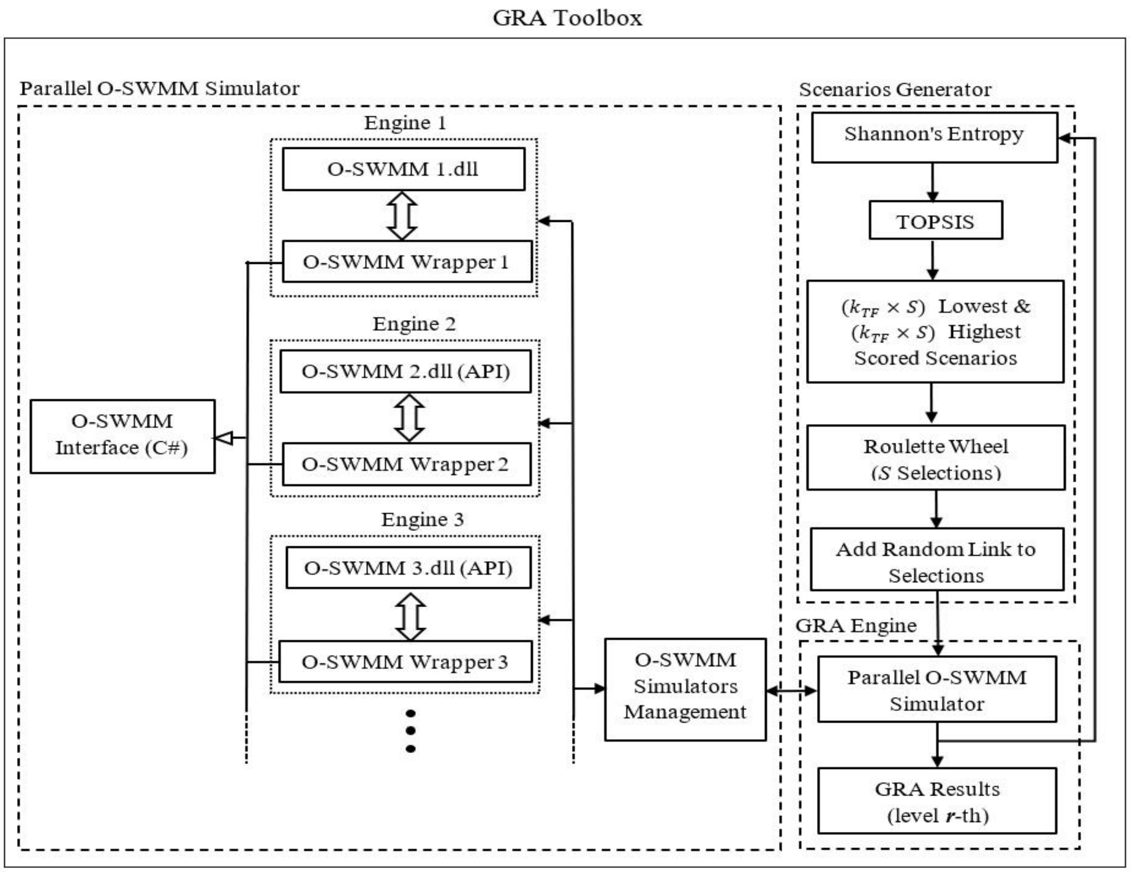

Figure 1: Block diagram of O-SWMM Toolbox

2.1 Parallel O-SWMM

2.1.1 Optimized-SWMM

SWMM is a dynamic rainfall-runoff model which has been developed by USEPA to simulate the performance of urban drainage and sewer networks. Although, its graphical interface simplifies usage of this engine, but it cannot be used in GRA because it requires multiple runs of model simulation. This justifies the utilization of SWMM engine (e.g., SWMM5.exe or SWMM API[3]) in an auxiliary software. Macro et al (2019) used this method to develop a tool for connecting

[3] An Application Programming Interface (API) is a collection of entry functions included in the software interface that allows external applications to call them directly for interacting with software components.

SWMM.exe[4] engine and an optimization software in order to implement green infrastructure. Banik et al (2014) developed a SWMM toolkit based on SWMM API for sewer systems to identify pollution source using genetic algorithm. In SWMM API, a number of exportable functions[5] have been provided to communicate with SWMM engine before, during and after a model simulation. Riano-Briceno et al (2016) presented an open-source toolbox named as MatSWMM in which some getters, setters[6] and data management functions were developed, because they needed to modify the setting of several orifices during the simulation and create for example a graph data structure from the network. Therefore, to change parameter values such as link properties during simulation and also tailor the outputs to suit specific needs, new exportable functions should be defined in SWMM engine. Moreover, in this engine there is no way to manage output file's content such as simulation's report file. If there are some getter functions by which the values of the desired variables can be obtained, then there is no need to report file or at least it can be summarized. Writing in a file is also a time-consuming part in each program; especially, when it needs to be repeated several times or is required to be shared among parallel processors.

However, Open Water Analytics group [http://wateranalytics.org] provided a series of exportable functions to customize the use of SWMM engine, but new exportable functions are proposed in our developed engine called Optimized-SWMM (O-SWMM) to get and set the value of some attributes before and also during the simulations (Table 1). Moreover, two report file management functions were considered to reduce hard drive overhead.

[4] SWMM.exe is executable SWMM engine which can be executed directly or run by an auxiliary application in windows.
[5] Exportable function is a type of functions which are defined in the software API for using by external applications.
[6] Getters and setters are API's functions (accessor properties) which are used for accessing value of properties and modifying their values.

The swmm_setLinkGeom function which sets the geometry parameters of a link was first proposed by Martínez-Solano et al. (2016) based on EPA SWMM 5.0.022 source code, but their library is not open source and does not work with input files[7] created by new versions of SWMM. The proposed O-SWMM was developed based on EPA SWMM 5.1.013 source code. Its possibility of changing Manning's n or pipe diameter before and also during simulation can be used in evaluating completely failure scenarios (such as GRA) or partial failure scenarios which are considered in the design of sewer networks to achieve better performance. In the GRA result section, this possibility is used and also significant reduction in simulation time and reducing volume of data needing to be written to the hard disk is reported using O-SWMM API.

Functions	Description
swmm_getLinkGeom	Gets values of xsection parameters
swmm_setLinkGeom	Sets values of xsection parameters
swmm_getConduitLinkRoughness	Gets Roughness (Manning's n) of a conduit
swmm_setConduitLinkRoughness	Sets Roughness (Manning's n) of a conduit
swmm_setAverageDWFChangingCoef	Sets a specific coefficient to change DWF inflow
swmm_getLinkXsectType	Gets link's xsection type
swmm_getObjectCount	Gets count of specific type of SWMM objects (nodes, links…)
swmm_getRouteModel	Gets flow routing method
swmm_getNodeInflow	Gets total inflow volume to a node
swmm_getOccuredNodeFlooding	Determines whether there has been a flood in the nodes so far
swmm_setGenerateReportFile	Determines whether the report file is generated or not
swmm_setReportFlags	Sets report flags to determine which parts should be included in the report file

Table 1: Functions included in O-SWMM Toolbox

[7] The input (.inp) file is the file format for SWMM. It contains the wastewater network propertices and simulation parameters.

2.1.2 Parallel Implementation

Some efforts have been made to parallelize the SWMM engine to increase the simulation speed of sewer systems (Burgess et al. 2000, Burger et al. (2014)). Burger et al. (2014) have considered four options of parallelization: multiple models, multiple events, multiple time step computation and multiple algorithms. They focused on the third option in which computation of conduits within a time step is distributed among available cores. The results show that the simulation time is decreased by 6 to 10 times on a twelve-core system. However, they estimated that the maximum speedup that can be achieved on any system is about 15 times regardless of the number of available threads. But, Mair et al., (2014) showed that by using first option for simulating several independent models, the result of parallelism is globally close to optimal time. In this parallelism level, the number of concurrent simulations and degree of speed increases are directly related to number of available cores and total time of simulating is absolutely reduced by adding number of cores. Therefore, in Parallel O-SWMM block, this parallelism structure was adopted to simulate independent scenarios in each GRA failure level.

In Parallel O-SWMM block, the number of concurrent executable simulations depends on available logical processors. Logical processors are the number of cores times the number of threads that can run on each core through the use of hyperthreading. Management of these logical processors is performed by the O-SWMM engine's management block. Whenever a logical processor is released, the O-SWMM engine's management block assigns another simulation scenario to that logical processor. For implementing this ability in Visual Studio, all of the O-SWMM wrappers in the block inherit from an object named O-SWMM interface and each of them is communicated to its own O-SWMM.dll API (Fig. 1).

2.2 Scenario Generation

One of the advantages of GRA method is evaluating system performance in a wide range of hydraulic failure scenarios. Considering each link has two possible cases: non-failed and complete failure cases, the total number of conduit failure scenarios in the entire solution space is calculated as:

$$F(N, c_i) = \sum_r \frac{N!}{(N-r)!r!} \qquad r = 1, \dots, N \qquad \textbf{(1)}$$

where r and N are the failure level and the total number of sewer network's links, respectively.

In real sewer networks, considering all possible combinations of conduit failure makes the computation very time consuming or even impossible. One of the possible solutions is to generate scenarios randomly. In this method, interdependent network components (links) are blocked randomly with equal failure probability for all components (Almoghathawi et al. 2019). Mugume et al. (2015) showed that for an 81-link urban drainage system (UDS), by considering more than 200 random failure scenarios the deviation percentage of GRA results are not significant, in all failure levels. It means that, for each failure level if a sufficient number of scenarios are selected randomly, the average resilience for them is approximately equal to the average resilience of all possible scenarios for that failure level.

All possible scenarios of each failure level can be divided into two sets. The first set includes the extreme scenarios also called strategical scenarios of that failure level in this paper, are scenarios where the resilience function takes on an extreme value. But, the second set includes scenarios whose resilience values are close to each other. This set can be generated using the random method proposed by Mugume et al. (2015). Therefore, in order to obtain more accurate GRA results with affordable time and computational cost it is necessary to use an efficient scenario selection method which is able to discover the extreme scenarios (first set) in each failure level.

In this study, a simple multi criteria scenario selection method based on a roulette wheel is introduced to find scenarios which lead to the minimum and maximum resilience at each failure level. The Roulette/Spinning wheel (RW) method as a selection operator is often used in genetic and evolutionary algorithms. In this method, a slice of the wheel is assigned to each individual, according to its fitness. In the presented GRA toolbox, each scenario in any failure level plays the role of the individuals. The extreme scenarios from individuals of one failure level are named as strategical scenarios, because these scenarios participate in generating individuals of the next failure level. The goal is that the scenarios generated for the next failure level include the extreme scenarios of the current level.

In each failure level, the probability of a scenario being strategic is estimated by a RW's fitness function. In sewer networks, the fitness function can be resilience but it should not be used for evaluating scenarios when multi-criteria participate in scoring scenarios. For example, suppose that a number of scenarios in a failure level have the same resilience based on function of the flood volume and failure time terms. So, if this function is used as fitness function, then these scenarios have the same slice size in RW. But they may have different flooding loss and failure time values, individually. Under this same condition, the weights of terms are usually determined in order to use in a Multi-Criteria Decision Making (MCDM) method using experimental studies based on questionnaire results or entropy, the Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), or Best Worst Method (BWM) methods (Maghsoodi et al. 2018). In this paper, the entropy method which was proposed in 1948 by Shannon (Shannon, 1948) is used, because it can quantify the amount of information in each criterion based on the criterion values distribution. The criterion with more entropy is more important. So, the weight of this criterion in fitness function method is more than weights of other criteria (Long et al. 2019). Then scenarios are scored based on a fitness function such as the Technique of Order Preference Similarity to the Ideal Solution (TOPSIS) (Hwang et al, 1993). In this method, first a positive ideal and a negative ideal solution were found and then the distance of each option from these solutions are calculated based on criteria values. The criteria can be positive or negative in nature. Wang et al. (2017) proposed a new framework based on TOPSIS to support decision making in sustainable drainage systems scheme design. For this, they used 12 criteria such as resilience, hydraulic performance and costs.

In the proposed GRA scenario selection method, the aim is to look for scenarios that are close to negative or positive ideal solutions. So, scenarios with lowest and highest scores are preferred. But this method requires a pre-processing step to determine the weights of the criteria.

According to these concepts, the GRA scenario selection algorithm includes the following steps at failure level r (Fig. 1):

1. Assuming that S scenarios were simulated at failure level $\mathrm{r}-1$, the weights of criteria using Shannon entropy are determined.
2. The S scenarios are scored using TOPSIS method with respect to criteria weights obtained from previous step. The fitness scores are normalized between 0 to 1.
3. $k_{TF} \times S$ number of these scenarios with the lowest scores and $k_{TF} \times S$ with the highest scores are selected, where k_{TF} is an arbitrary coefficient between 0 and 1. These two sets of scenarios are participated in scenario generation process of next failure level r.

   Notice: In the first failure level, all the possible scenarios are considered and simulated.
4. The roulette wheel is generated based on fitness scores of the selected scenarios. For the scenarios with highest scores, the size of slices is equal to the scores, but for the scenarios with the lowest scores, the size of slices is equal to the $1 - score$. This is because the

probability of choosing them must be equal to the probability of choosing the scenarios with the highest scores in the proposed selection method.

5. A random scenario is selected from the generated roulette wheel. This candidate is a combination of $\mathrm{r}-1$ conduits.
6. A random conduit (except of the conduits in the candidate scenario) is added to the scenario in order to generate scenario of the next failure level.
7. Steps 5 and 6 are repeated to generate a set of S distinct scenarios of the failure level r.

It should be mentioned that for simple sewer network, value of S at each failure level r can be the number of distinct r-combinations of conduits, obtained from Eq.1. But for complex networks, value of S can be a fixed value for all failure. Although, the number of distinct r-combinations of conduits at failure levels 1, $N-1$ and N are equal to N, N and 1, respectively. In these failure levels, all of the combinations are simulated by the GRA toolbox.

2.3 GRA Engine

After generating S scenarios for a failure level, these scenarios are simulated by parallel O-SWMM simulator. Then, resilience is calculated for each of these scenarios by a predefined resilience formula proposed by Mugume et al., (2015):

$$Res_i = 1 - \sum_{j=1}^{n} \left[\frac{V_{F_j}}{V_T} \times \frac{t_{F_j}}{t_T} \right] \quad , i = 1, \dots, S \qquad \textbf{(2)}$$

where i and j are number of scenarios in each failure level and number of flooded nodes in each scenario, respectively. $\mathrm{V_T}$ and $\mathrm{V_{F_j}}$ are the total inflow volume and the flood volume occurred in node j, respectively. $\mathrm{t_{F_j}}$ is failure duration of node j and $\mathrm{t_T}$ is simulation time. It should be noted that this equation is used to verify the toolbox performance, and can be substituted by another formula upon need. For example, Nan and Sansavini (2017) proposed a metric which integrates six measures defined based on system resilience transitions in order to evaluate the resilience in interdependent infrastructures. Sharma et al. (2018) proposed simple metrics (e.g., Center of Resilience and Resilience Bandwidth) that decompose the recovery curve for resilience quantification. Moreover, Wang et al. (2019) presented a new approach for assessing resilience of urban drainage systems using resilience profile graph which unify the concepts and metrics of reliability, robustness, resilience and failure. Cheng et al. (2021) reviewed the resilience metrics, along with their limitations and applicable scenarios. They developed multimodal resilience metrics including instantaneous resilience at specific time instants, overall resilience and average resilience over a time period. The system reliability, average robustness and average recovery ability were considered in their proposed metrics.

Finally, the minimum, mean and maximum of these resilience values are calculated for each failure level. When this process was executed for all failure levels, the global resilience is illustrated vs failure levels.

3. Results and discussion

Figure 2 shows proposed toolbox user interface which has two tabs for simulating and analyzing GRA results. Two types of blockage simulations can be considered on conduits by setting a non-zero value for changing diameter or roughness parameters located in properties section. Start and end time of failure are specified by failure start time and failure end time parameters based on exportable function of O-SWMM API. Moreover, by changing the inflow (DWF) coefficient parameter, the inflow values to the manholes can be increased or decreased in order to investigate its effect on the resilience. The number of scenarios simulated in parallel is adjusted by logical processors parameter and the value of S and k_{TF} related to scenarios generator block can be adjusted in the properties section. In the links section, based on a predefined conduit naming rule it can be specified which conduits can participate in the scenario generation process. This feature is useful for extracting network skeleton from large urban sewage networks in order to decrease number of possible scenarios.

Four different types of GRA simulation (GRA based on simulating all scenarios using swmm.exe or O-SWMM API and also GRA based on simulating scenarios selected by two different methods: proposed roulette wheel and random selection methods) were implemented on the toolbox and used for analyzing two test cases to evaluate the performance of its blocks (Fig. 2). All processes executed using a laptop with the Intel(R) Core ™ i7- 9750H CPU @ 2.60 GHz and 8GB RAM. According to its CPU architecture, 10 out of the 12 available logical processors were allocated to the Parallel O-SWMM block.

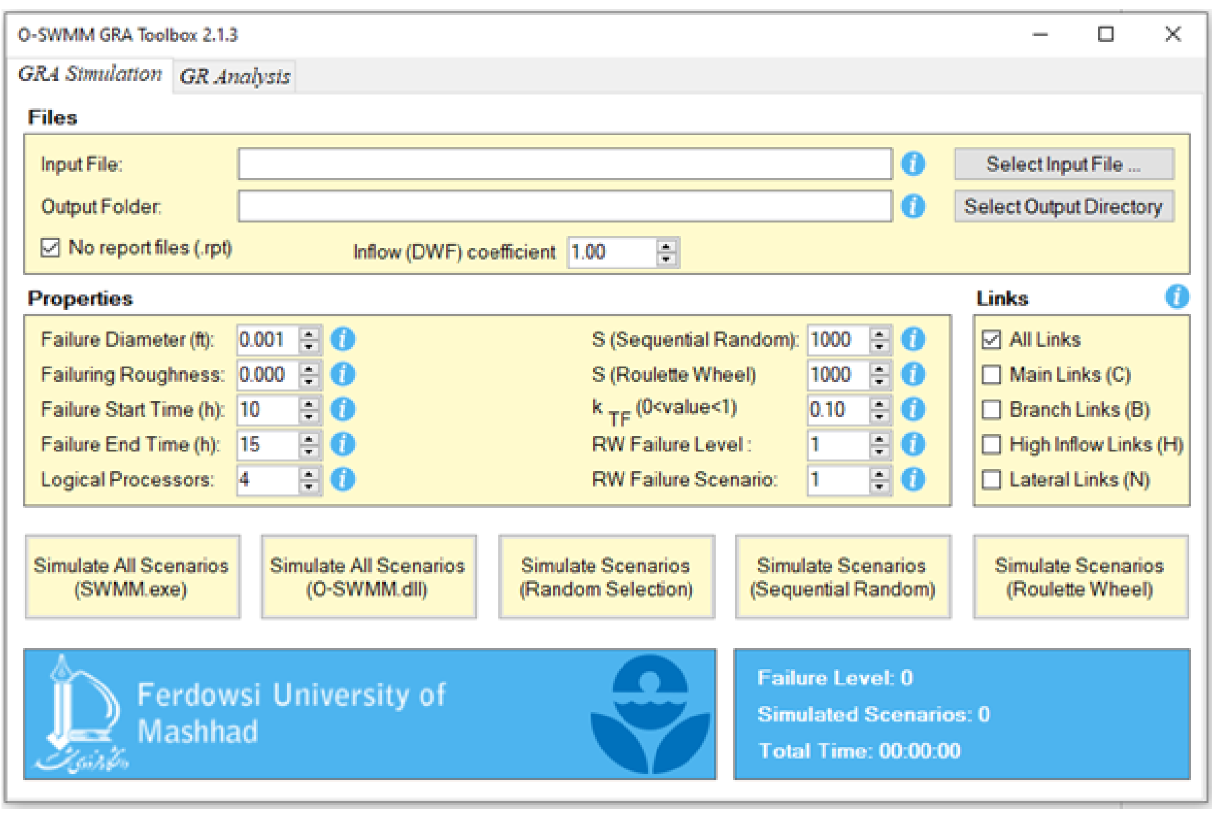

Figure 2: O-SWMM Toolbox User Interface

3.1 Evaluation of O-SWMM API

In the first experiment, an example network of EPA-SWMM's manual (Gironás et al. 2010) was used to evaluate functionality of O-SWMM API compared to the original SWMM application (swmm.exe). Figure 3 shows a schematic view of the test case which includes a 29-hectare area and variety of objects such as storage units, orifices, weirs and two typical Low Impact Developments (LID).

Figure 3: Sample combined sewer system for toolbox validation

The network contains 20 nodes, 18 conduits and 24 sub catchments. Due to small number of conduits, all possible combinations of failed links can be simulated in a fairly short time. Therefore, 262,143 simulations were performed using both EPA-SWMM and O-SWMM API for a 48-hour. Moreover, the 100-year return period storm is selected from three existed events in order to simulate an exceptional condition.

To run the EPA-SWMM similar to O-SWMM API, a C# auxiliary application was developed such that multiple copies of swmm.exe could be run in a parallel manner. The structure of this application is similar to “Parallel O-SWMM” block. For each failure scenario, a logical processor generated an input file by modifying the roughness values of selected conduits to 100 in the original input file and saved it on hard disk. Then, the related copy of swmm.exe was used to simulate the generated input file (.inp) and the result was recorded in a report file [8](.rpt). When the simulation of a scenario was completed, the report file was read by the logical processor to extract the required information for GRA calculation. The same process was repeated for O-SWMM API, except that by using proposed exportable functions, there was no need to further process for generating input files and also writing and reading report files (.rpt). The roughness of selected conduits was modified to 100 during runtime by using “swmm_setConduitLinkRoughness” exportable function. It should be noted that, for accurate comparison the “reporting options” property in original input file was set to “NONE” in order to decrease the process time of swmm.exe simulation tools.

The execution time and size of written data for two simulation tools are shown in Table 2. As it can be seen, the written data and consequently execution time are significantly decreased by using O-SWMM API. When the SWMM.exe is used for global resilience analysis, the execution time and size of written data is increased for each scenario simulation. Therefore, speed of processing is slowed down because of file access. There are two clear reasons for this:

1. It is required that the input file is generated and written on the hard disk for each scenario simulation. Because, each scenario has different conduits properties (diameter or Manning's n).

[8] The report file is a plain text file in which SWMM simulation results include status and summary results reports are written.

2. The results of each simulation (.rpt file) are written on the hard disk by EPA SWMM and then the GRA toolbox must be read the file in order to calculate resilience of each scenario based on the total flooding loss and the flooding time.

These two time-consuming operations which have programming processing and also hard disk usage are eliminated if the proposed exportable functions of O-SWMM API are used. Since conduits properties are changed by swmm_setLinkGeom or swmm_setConduitLinkRoughness functions, a unique input file for all scenarios is needed. After each simulation, the total flooding loss and the flooding time is gotten using API functions, directly. So, we disabled writing report file on hard disk by swmm_setGenerateReportFile proposed exportable function.

	Total Execution Time (min)	Data Written on Disk (MB)
SWMM.exe	806.15	18673
O-SWMM API	317.80	29

Table 2: Computational cost comparing between O-SWMM API and EPA-SWMM

In addition to computational cost, the GRA values calculated based on simulation results of O-SWMM API and SWMM.exe were compared in order to evaluate performance accuracy of the developed exportable functions of O-SWMM API. Figure 4 shows minimum, mean and maximum of resilience values computed based on Eq. 2, at each failure level. The root mean square error between obtained mean resilience values using two simulation tools was equal to $1.2275\ e-11$.

As the number of failed conduits increases, resilience is expected to decrease, but the results show an increasing trend of the minimum resilience from failure level 4, in the sample network. To investigate the rationale behind, two scenarios named as scenarios “A” and “B” were considered.

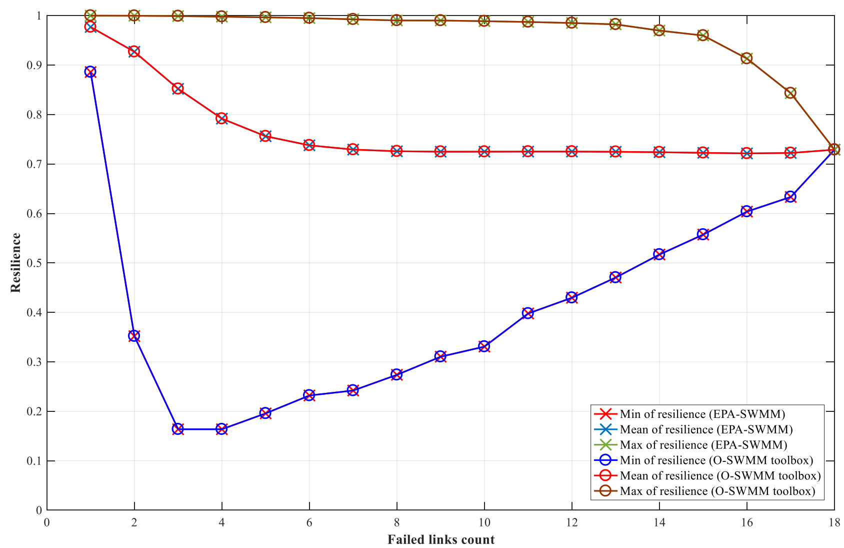

Figure 4: Comparison of calculated resilience by EPA-SWMM and O-SWMM API

In the first scenario, conduit C4 was failed in two days. In the second scenario, conduit C4 and C3 were failed during same simulation time. In this sample network, junction depth of all three nodes J15, J3 and J4 is 3 ft. These conduits and nodes are shown in figure 3. The simulation results showed that in both scenarios one of these nodes was flooded, node J4 in scenario A and node J3 in scenario B. In the second scenario, the failure time was less than first one. The failure interval for each scenario is shown in figure 5 with a red highlight and it is about 1.42 and 1.16 hours for scenario A and B, respectively. Moreover, the total flood volume of scenario A is higher than scenario B. The flood volume for these scenarios was $12E4$ gallons and $4E4$ gallons, respectively. Therefore, according to equation 2 the resilience of scenario A with one failed conduit is less than scenario B in which two conduits were failed.

In this example, there were two reasons for increased resilience with increasing number of failed conduits. First, non-failed conduits can act as storage reservoir when other conduits are failed and retain some of the inflow. In the scenario B, conduit C15 stored about 33000 gallons during simulation time and a smaller amount of inflow entered to J4 because failed conduit C3 was not able to transfer sewage effluent. So, unlike to the scenario A flooding loss did not occur in J4. This was the second reason for the resilience increasing.

The node depth of the sewage effluent in three junctions J3, J4 and J15 during simulation time are shown in figure 5. The red dashed line shows allowed depth of effluent in these junctions. As it can be seen, the height of the sewage effluent in junction J3 is equal to the depth of this junction almost all along the simulation time. But, flooding loss at this junction is not occurred after 02:30 on the first day, because the total inflow entered to this junction is zero from this time until the end of the simulation.

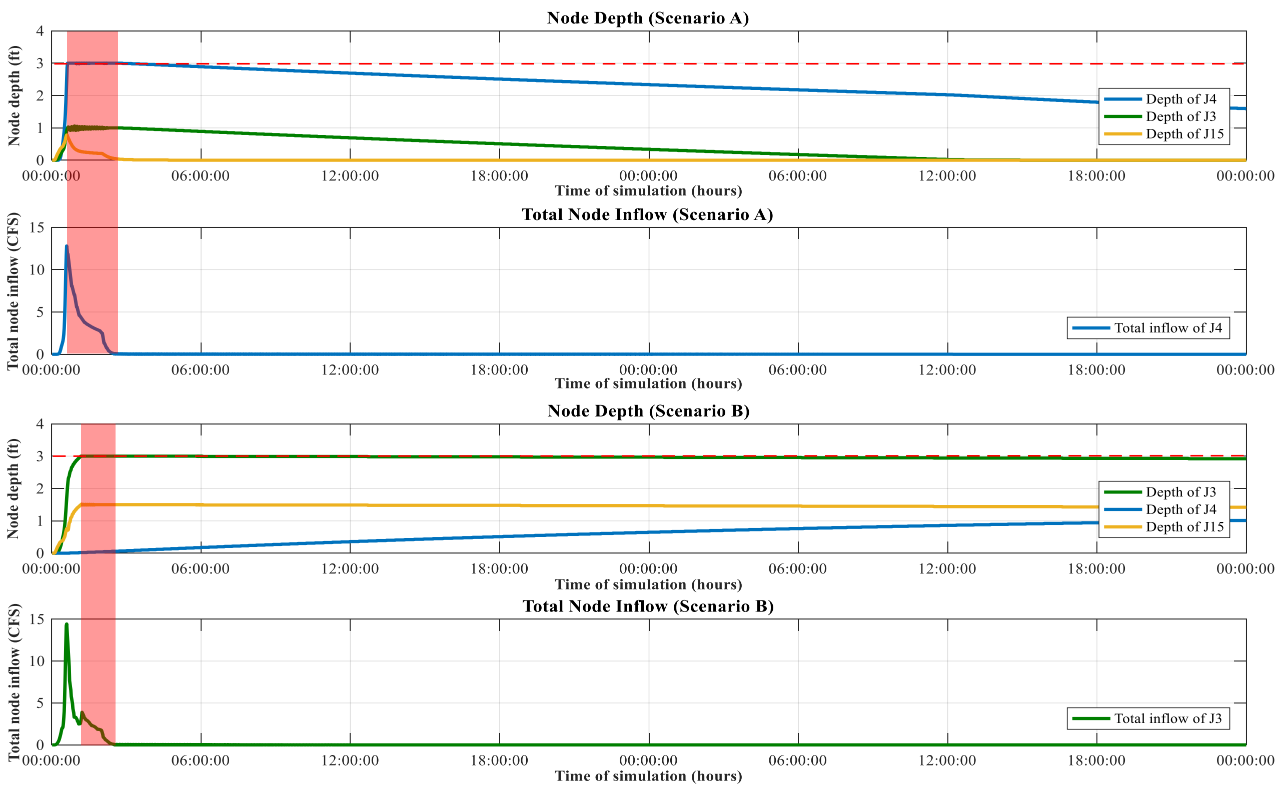

Figure 5: Comparison of node depth and total inflow in two scenario A (blockage in C4) and B, (blockage in C3 and C4).

3.2 Evaluation of Scenario Selection Approach

To evaluate the proposed scenario selection method, the GRA results were compared with GRA results of simulating all possible scenarios in the mentioned sample network and also in a real sewer network.

In the first step, the toolbox was run to analyze global resilience of the sample network. The values of S and k_{TF} were considered to be 100 and 0.1 in the proposed scenario selection method. Moreover, two criteria (total flooding loss and mean failure time) were considered in Shannon entropy and TOPSIS processes to score simulated scenarios. The GRA results with this approach were then compared with all possible scenarios results (Figure 6). The minimum, mean and maximum resilience for the sample sewer network was estimated by proposed method with RMSE equal to 0.12, 0.08 and 0.02 which are quite satisfactory.

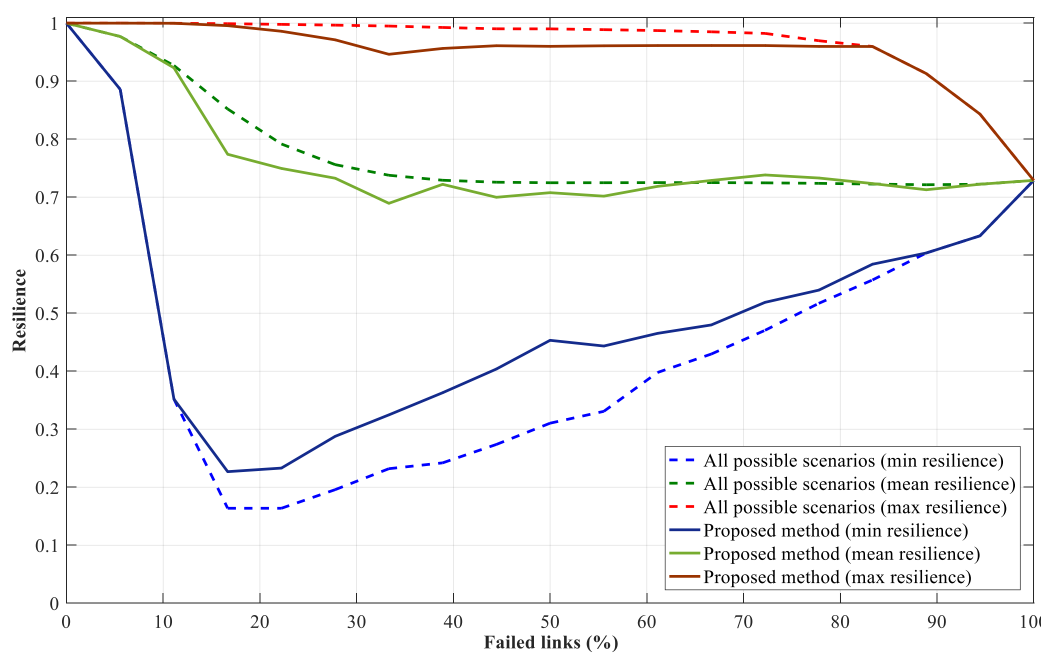

Figure 6: Comparison of GRA results obtained from proposed selection method and all possible scenarios simulation for the sample sewer network.

Then performance of the presented GRA toolbox was evaluated in a real separate sewer system for sanitary, a town in the north east of Iran. This fairly complex network (figure 7), consists of 1005 conduits and 999 nodes and designed for 42,000 citizens. Firstly, to make the simulation of all possible scenarios achievable, 20 zones were identified in the network and their outlet conduits were selected as representative conduits which participate in the failure scenarios. Figure 7 shows these 20 zones in different colors and red circles represent conduits participated in GRA.

Figure 7: The real sewer network in Iran. The red circles indicate the representative links of each zone.

According to these 20 conduits, all 1,048,575 possible scenarios were simulated and GRA results were calculated based on Eq. 2. The toolbox was then run in which the values of S and k_{TF} were considered to be 100 and 0.1. The total flooding loss and mean failure time criteria were considered in Shannon entropy and TOPSIS processes. Figure 8 has compared GRA results calculated by selected scenarios using proposed method with all possible scenarios values. The minimum, mean and maximum resilience for the real sewer network was estimated with RMSE of 0.033, 0.022 and 0.002 by simulating 20×100 scenarios, in overall.

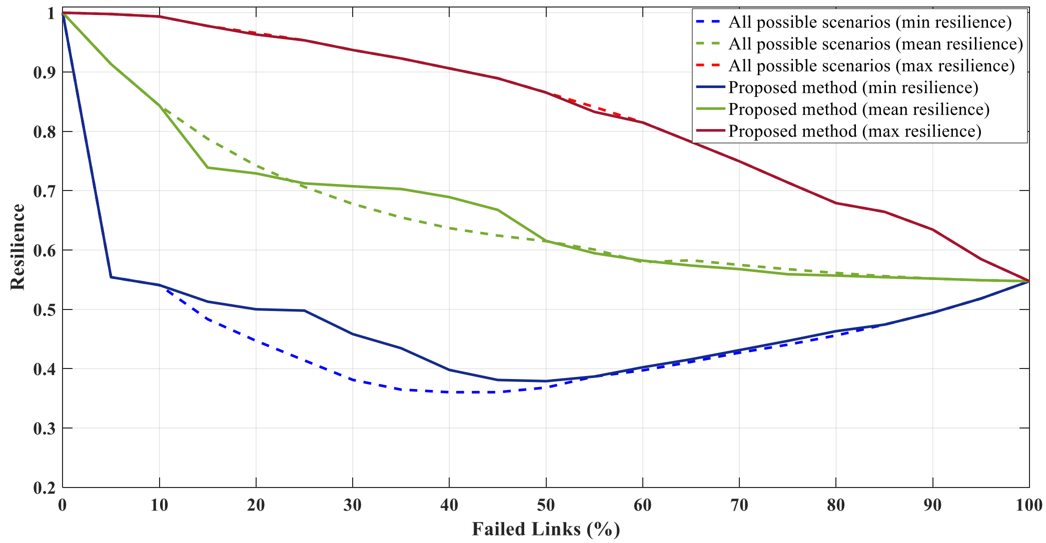

Figure 8: Comparison of GRA results obtained from proposed selection method and all possible scenarios simulation for the real sewer network.

3.3 Evaluation of the Toolbox

In the final evaluation, out of 1005 existing conduits, 275 conduits (network skeleton) were selected to be participated in analyzing global resilience by the toolbox. These conduits consisted of main transmission line, collectors and pipes in the main streets which selected based on an engineering judgment. Noteworthy that all conduits were participated in the network simulation but the link blockage (failure) was assumed to be occurred in these 275 conduits.

A standard sewage daily pattern was used to determine the peak time of sewage inflow to evaluate the network performance in critical situations. Figure 9 shows the dry weather inflow and the outfall diagrams in which the highest rate of network input occurs in the time interval from 10 am to 3 pm. Therefore, at this time interval in each scenario simulation, the roughness of selected conduits was increased to 100 during runtime by using “swmm_setConduitLinkRoughness” exportable function of O-SWMM API.

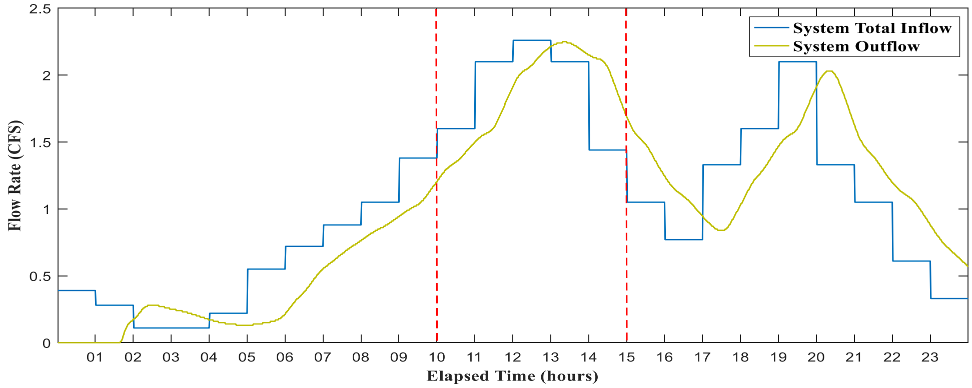

Figure 9: Dry weather inflow and the outfall diagrams. The dashed red lines show failure interval

In this experiment, simulating the total number of all possible scenarios could take long time, because all 275 conduits were participated in analyzing global resilience. Therefore, performance of proposed scenarios selection method was evaluated by comparing it's results with GRA results obtained using random scenarios selection method proposed by Mugume et al. (2015). To analyze the global resilience, Mugume et al. (2015) used a convergence analysis to determine the minimum required number of scenarios for different failure levels. For a comprehensive comparison, this convergence method was also performed in this section to determine the value of S, in our proposed method.

3.3.1 Convergence Analysis

For convergence analysis and determining the value of S, the following steps were taken.

1) Seven different set were simulated which are: 5 random sequences (5 scenarios × 275 failure levels), 10 (2750 failure scenarios), 25 (6,875 failure scenarios), 50 (13,750 failure scenarios), 100 (27500 failure scenarios), 200 (55,000 failure scenarios), 500 (137,500 failure scenarios), 1000 (275000 failure scenarios).

2) The mean of the total flood volume in each failure level was determined for all random sequence sets.

3) The percentage deviation between each consecutive set was calculated based on the computed mean values, i.e., deviation between {5,10}; {10, 25}; {25,50}; {50,100}; {100,200}; {200,500}; {500,1000}.

Figure 10 shows the result of convergence analysis for the sets. For the first time, a convergence was obtained in set {50,100}. The maximum deviation of this set was 8.53%. In the three other sets, the maximum deviation was also reduced to 6.96%, 5.54% and 4.81%, respectively.

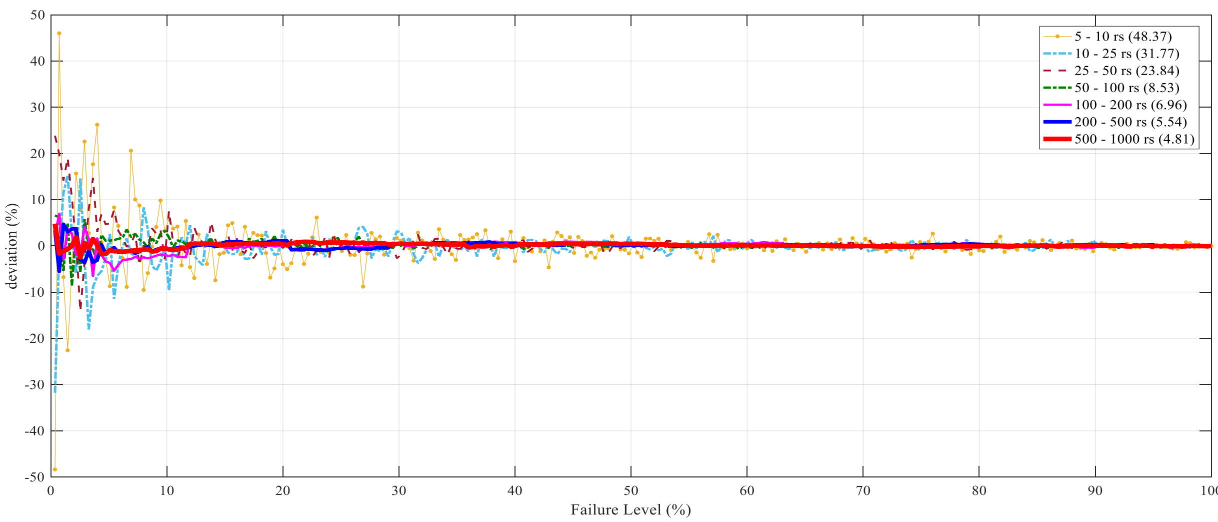

Figure 10: Convergence of GRA results for random links failure sequences

3.3.2 Performance Evaluation

Based on the obtained deviation results, the value of S was considered as 1000. The value of k_{TF} like previous experiments was set to 0.1; thus 200 strategical scenarios (100-minimum and 100-maximum points of RW fitness function) participated in selecting scenarios of the next failure level to generate first set of scenarios. Moreover, 1000 scenarios in each failure level were selected randomly in order to generate second set of scenarios. To evaluate the performance of the proposed scenario selection method, the GRA results of two generated sets are shown in fig. 11, separately. The results showed that the minimum and maximum of GRA calculated by the proposed method are significantly different from random selection results. The pattern of mean resilience resulted by using these two methods is also different. In the random selection results, the mean resilience has an increasing trend from 28% to 53% of failed links. But, the mean resilience in the proposed selection method has a sharp decrease at around 60% of failed links and before and after this point the resilience is decreasing with a slight slope. A convergence analysis method was used to determine the minimum required number of scenarios for each failure level, but finding and considering the extremum points of the resilience in each failure level can make more accurate GRA result, when a trade-off between execution time and reliability of result is inevitable. Moreover, the equation 2 is only used to calculate resilience of scenarios selected by two methods in order to compare their GRA results. But if another model (formula) is used to calculate the resilience, the variables of that formula should be used as criteria in TOPSIS, when our proposed scenario selection method is used.

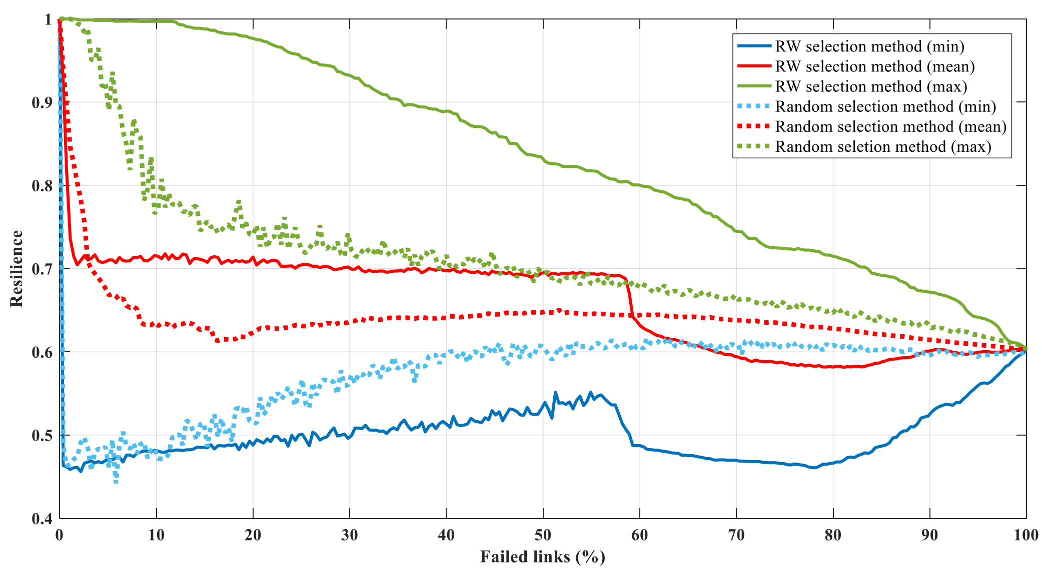

Figure 11: Comparison of GRA results generated using the proposed roulette wheel and the random selection methods

Simulation of each failure scenario of the real sewer network alone takes 107 seconds, if the original SWMM is used. According to 275 conduits, the total number of all possible scenarios is around $6.07\ e + 82$ and simulating this number of scenarios could take long time around $9\ e + 75$ years. But, $2.75\text{e}5$ failure scenarios were only simulated by presented GRA toolbox based on RW scenario selection method. If the original SWMM is used, simulating this number of scenarios in parallel manner takes about 34 days, using 10 logical processors. But the proposed toolbox analyzed global resilience of the network just in 15 days using O-SWMM API which reduced the execution time by 56% (2.26 times faster).

4. Conclusions

In this article, an open-source toolbox was presented for investigating functional resilience in sewer networks based on GRA. To properly cover the large space of failure scenarios that is a challenge in the real networks, a simple method is proposed based on the roulette wheel to identify the most strategical combination of failed pipes in each failure level. For two case studies (sample and real networks), the global resilience was estimated by simulating a small number of scenarios with RMSE 0.025 and 0.022 comparing with simulating all possible scenarios. Moreover, using O-SWMM API which is an optimized development of EPA's SWMM, the GRA execution was 2.5 and 2.26 times faster.

The proposed API provides the ability to modify roughness and links properties during simulation to simulate quantitative failures. Future work will focus on developing O-SWMM API to modify quality parameters in order to analyze global resilience of the system to sewage quality disturbance.

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