Events group risk importance by genetic algorithms

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Abstract: In this paper, the power of genetic algorithms is exploited to search for the most important groups of events in a risk/reliability model. To this end a two-objective search is formulated in which the decision variables are the groups of events, and the objectives are to maximize the importance of the groups, while minimizing their dimension. This allows the identification of the most important single events, couples of events, triplets, and so forth. Three case studies concerning network systems of increasing complexity are analysed.

Keywords: group importance measures, Fussell–Vesely importance measure, differential importance measure, multi-objective optimization, multi-objective genetic algorithms, network systems, redundancy allocation

1 INTRODUCTION

The importance measures (IMs) currently used in reliability and risk analysis [**1**, **2**] quantify the impact of single failure or success events, occurring one at a time [**3**]. Yet, the influence of interactions of multiple failure events is fundamental with respect to the failure behaviour of the highly redundant and multi-state systems typically encountered in practice. For example, different basic events may represent different modes of failure or unavailability of a single component, and in order to determine the importance of such a component, one has to consider all the related basic events as a group. Furthermore, many risk-informed applications deal with evaluating the risk change associated with changes in the plant technical specifications (surveillance and/or test frequencies, etc.); such changes may indeed impact upon a group of components. Further, system upgrades such as components renewal, replacement, or redundancy allocation may involve multiple components simultaneously. These interventions must be prioritized on the most important groups of components, in order to use effectively the budget available.

Some practical difficulties arise when evaluating the importance of groups of components. Indeed, for the most commonly used importance measures, the importance of groups of components cannot be quantified directly from the importance of the individual components making the group [**3**]. Instead, the system must be reanalysed to evaluate the importance of each group, leading to an intractable combinatorial explosion. This may, for example, entail rerunning a complete system simulation code to evaluate the impact on the system of multiple failure events. Note that the Fussell–Vesely (FV) IM makes notable exception: the FV importance of a component is the sum of the FV importances of the basic events modelling the failure modes of that component, when the basic events do not appear together in any minimal cut set [**4**].

An attempt partially to overcome this limitation has led to the introduction of the differential importance measure (DIM) for use in risk-informed decision making [**5**]. The DIM is a first-order sensitivity measure that ranks the parameters of the risk model according to the fraction of the total change in the risk that is due to a small change in the parameters' values, taken one at a time. The DIM bears an important property of additivity: the DIM of a group of components or basic events is the sum of the DIMs of the single components or basic events of the group. However, since DIM considers risk changes owing to small changes of the parameters' values, it does not fully account for interactions among components [**6**].

Computing the complete profile of the importance of all combinations or groups of events is not feasible,

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as this would lead to a combinatorial explosion of the number of possible combinations to be analysed, and would not necessarily be informative. This calls for an effort to prioritize the analysis only on the most important combinations of events. This challenge is the motivation behind the work described here.

In the current paper, genetic algorithms (GAs) are used to search for the most important combinations or groups of events. The problem is framed as a multi-objective search, in which the decision variables are the groups of events and the objectives are:

(a) to maximize the importance of the group;
(b) to minimize the dimension of the group.

This formulation guides the search towards the identification of the most important single events, couples of events, triplets, and so forth.

The paper is organized as follows. Section 2 presents the proposed optimization approach in more detail, along with the motivations which led the authors to choose GAs as the optimization tool. In section 3, the approach is demonstrated on a case study of a network system of literature (case study 1) [**7**], with reference to two importance measures, the DIM and the FV [**8**]. Section 4 presents the application to more complex network systems (case studies 2 and 3) [**9**]. Conclusions and directions for future work are presented at the end.

2 PROBLEM FORMULATION

Consider a system of N components and a generic importance measure IM. Depending on the cases, the measure IM gives different prioritizations of the components, measuring different effects of the components' performance on the system. For example, the FV importance measure of a component quantifies how much its failure contributes to the system failure.

Group IMs quantify the effect that the failure of all components in the group has on the system. The importance of a group of components is indicated as follows

$$IM(x_1, x_2, ..., x_N) \tag{1}$$

with $x_i = 1$ if i belongs to the group, $x_i = 0$ otherwise.

For example, in a system with $N = 3$ components, $IM(1, 0, 0)$ indicates the importance of the first component alone; $IM(0, 0, 1)$ indicates the importance of the third component alone; $IM(1, 0, 1)$ indicates the importance of the first and third components together, i.e. considered as a group. As mentioned in the introduction, except for the DIM, $IM(1, 0, 1) \neq IM(1, 0, 0) + IM(0, 0, 1)$ so that computing $IM(1, 0, 1)$ usually requires a complete reanalysis of the system [**3**].

In a system of N components, the number of groups (single components, pairs, triplets, and so forth) that in principle can be formed is 2^N. A complete importance analysis of all groups is therefore impractical for large systems and one needs to focus only on the most important groups of components. As mentioned in the introduction, the problem of determining the most important groups of components is framed in this paper as an optimization problem with respect to the two following objectives

$$\text{Max } f_1(\boldsymbol{x}) = IM(x_1, x_2, ..., x_N) \tag{2}$$

$$\text{Min } f_2(\boldsymbol{x}) = \sum_{i=1}^{N} x_i \tag{3}$$

with $x_i = 1$ if i belongs to the group, $x_i = 0$ otherwise.

The idea behind this formulation is that, trivially, the more components belong to the group, the more their impact on the system and therefore the higher their importance. A search directed only by the importance of the groups would then favour large groups containing many events, whose simultaneous occurrence is, however, less likely. On the other hand, introducing the second objective in favour of small groups should lead the search to finding the most important small-sized groups of components, i.e. the most important single events, couples of events, triplets, and so forth.

Note that in the formulation in equations (2) and (3), groups of components are evaluated with the IM referred to a single system performance measure (e.g. the system unavailability). Groups can in principle be evaluated considering multiple criteria of evaluation, e.g. the group importance with reference to another system performance measure (say revenues from operation) or purchase or maintenance cost of the components of the group. This would entail adding other objective functions to the formulation of equations (2) and (3). Future work will address these aspects.

Concerning the multi-objective problem, a common way to tackle this is by focusing the optimization on a single objective constituted by a weighted combination of some of the targets, while imposing some constraints to satisfy other targets and requirements [**10**]. This approach, however, introduces a strong arbitrariness in the a priori definition of the weights and constraints levels. A more informative approach is one which considers all individual targets separately, aiming at identifying a set of solutions which are equivalent in absence of an assigned ranking of the various objectives [**10**]. Each member of this set is better than or equal to the others of the set with respect to some, but not all, of the targets. Differently from the single-objective approach, the set identified by the multi-objective approach

provides a spectrum of 'acceptable' solutions among which a compromise may be found.

In this work, the multi-objective approach is used. Given the combinatorial number of potential alternatives, the problem is difficult to tackle with classical optimization methods, e.g. of the gradient–descent kind [**10**]. Moreover, these methods encounter severe difficulties when the objective functions to be optimized are embedded in a complicated computer code from which differential information is not easily retrieved. This is the case of the realistic, detailed models required to evaluate the risk/reliability/availability/profit performance of complex hazardous systems, such as nuclear power plants, for which adherence of the model to reality is mandatory owing to the severe safety implications.

For the above reasons, the current authors resort to GAs, which are computationally powerful numerical search tools operating according to procedures that resemble the principles of natural selection and genetics [**11**, **12**]. They are capable of handling multivariate, non-linear objective functions and constraints, and base their search simply on information relative to the objective functions to be optimized, with no need to evaluate any of the derivatives.

In recent years, an increasing number of GA applications to single-objective optimizations have been observed in the field of reliability, availability, maintainability, and safety analysis [**13–19**]. In a standard single-objective optimization, the GA proposes a set of candidate system design solutions, and the performance of each of them is measured through the value of an objective function, called fitness (e.g. either cost, with reliability constraints, or vice versa). The set of candidate solutions is then allowed to evolve according to probabilistic, 'genetic' rules, which effectively guide the search towards a near-optimal solution.

The extension of GAs to multi-objective optimization entails comparing two solutions with respect to the multiple objectives considered [**20–30**]. In the case of a single objective, the comparison is trivial: as explained above, a vector solution x is better than another one, say y, if the corresponding objective function (fitness) value $f(x)$ is greater than $f(y)$. When the optimization problem is extended to N_f objectives, there are N_f objective functions $f_i(\cdot)$, $i = 1, 2, \ldots, N_f$ to deal with and thus two solutions x and y must be compared in terms of *dominance* of one solution over the other with respect to all N_f objectives [**31**]. As a result of the multi-objective search process, convergence is achieved on a Pareto optimal set of non-dominated solutions, which represents the whole spectrum of information at the disposal for the decision maker to identify, a posteriori, his or her preferred solution.

Chromosome coding (10 bits)											
1	2	3	4	5	6	7	8	9	10		**Corresponding component group**
1	0	1	0	0	0	1	0	0	0		1,3,7
1	0	0	0	0	1	0	1	1	0		1,6,8,9

Fig. 1 Example of chromosome coding of component groups in a system of ten components

In the most typical applications of GAs, every proposal of solution, represented by the vector x of the independent decision variables (control parameters), is coded in a so-called chromosome, constituted by so-called genes, each one coding one decision variable of x; a binary coding is widely used. In a different way from these typical applications, the decision variables $(x_1, x_2, \ldots, x_N)$ of equation (2) of the optimization problem considered in this paper are already in the form of a binary string. Therefore, single-gene chromosomes are used, directly coding the composition of the group. The dimension of the chromosome is equal to the number of components in the system. Figure 1 shows an example of chromosome coding for a system of ten components.

3 CASE STUDY 1

Consider the network of Fig. 2 [**7**]. Table 1 reports the unavailability of each arc. The nodes of the network are assumed perfect, i.e. non-failing. The number of components in the system is ten; therefore, the total number of possible groups of components is 1024.

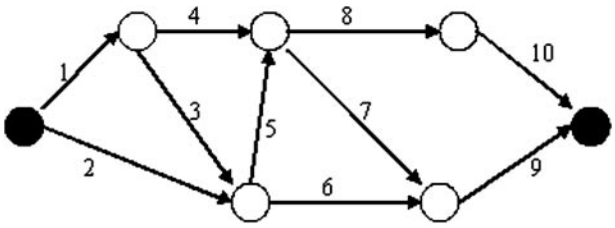

Fig. 2 Network configuration (case study 1)

Table 1 Unavailability, FV, and DIM importances of the arcs in the network of Fig. 2

Component	Unavailability	FV	DIM
1	1.39×10^{-1}	2.5×10^{-1}	6.6×10^{-2}
2	1.04×10^{-2}	5.4×10^{-2}	1.9×10^{-1}
3	4.86×10^{-2}	5.1×10^{-4}	3.2×10^{-4}
4	2.18×10^{-2}	3.3×10^{-2}	5.0×10^{-2}
5	1.87×10^{-1}	2.4×10^{-1}	4.4×10^{-2}
6	1.07×10^{-1}	1.7×10^{-1}	5.3×10^{-2}
7	8.39×10^{-2}	5.1×10^{-2}	2.0×10^{-2}
8	9.49×10^{-2}	4.5×10^{-1}	1.7×10^{-1}
9	1.22×10^{-1}	8.0×10^{-1}	2.5×10^{-1}
10	6.48×10^{-2}	3.1×10^{-1}	1.6×10^{-1}

Table 2 Minimal cut sets of the network of Fig. 2

Order of the minimal cut set	Elements of the minimal cut set
2	1, 2
	8, 9
	9, 10
3	1, 5, 6
	1, 5, 9
	2, 3, 4
	4, 5, 6
	4, 5, 9
	6, 7, 8
	6, 7, 10
4	2, 3, 7, 10

Table 3 Genetic algorithm parameters and rules

	Case 1	Case 2
Number of chromosomes (population size)	10	50
Number of generations (termination criterion)	50	10
Selection	Fit–Fit	Fit–Fit
Replacement	Children–parents	Children–parents
Mutation probability	0.001	0.001
Crossover probability	1	1
Number of generations without elitist selection	15	15
Fraction of parents chosen with elitist selection	0.25	0.25

The minimal cut sets of the network are listed in Table 2.

The optimization approach proposed in the previous section has been applied with respect to two importance measures referred to the unavailability of the system, the DIM and the FV. The system unavailability is computed as the union of the minimal cut sets. The two applications to the DIM and the FV are discussed separately in what follows. The results have been obtained by the user-friendly, multi-purpose, multi-objective genetic algorithm (MOGA) code developed at the Department of Energy of the Polytechnic of Milan, Italy (see http://lasar.cesnef.polimi.it).

3.1 Application to the DIM

When referred to the system unavailability, expressed as a function of the components' unavailabilities, the DIM measures how far changes in the components' unavailability result in changes in the system unavailability [**5**]. When applied to groups of components, the DIM evaluates how far changes in the unavailability of the components of the group result in changes in the system unavailability. Note that the DIM is additive, so that for each chromosome the importance of the corresponding group (i.e. the objective function f_1 of equation (2)) is obtained by adding the values of the DIMs of the components making up the group.

Different trials were performed to determine the adequate GA parameters and rules. Table 3 reports two such cases performed to evaluate the effect of the population size (i.e. the size of the evolving set of candidate solutions) and of the number of generations (i.e. the duration of the evolution process) in the particular optimization problem. In order to evaluate the repeatability of the results, five optimization runs were performed for each case, starting from different initial random populations. It is important to note that in both cases very few of the performed runs were able to find the complete Pareto optimal set, inclusive of the ten most important groups, one for each of the ten possible sizes (i.e. from one to ten components). Usually, the number of solutions found by the search was around 6–8 (i.e. 6–8 different group sizes). In order to obtain the complete Pareto set of ten groups, it was necessary to aggregate the results from the five different runs. This suggests that the optimization strategies used do not allow the whole Pareto front to be covered well, and this calls for an increase of the genetic diversity in the population. A way to do this could be to induce niches in the evolution [**32**]. Future work will be devoted to this particular aspect.

Figure 3 shows the results obtained in the two cases in Table 3 (top and bottom, respectively). In the figure, the values of the objective functions are reported in correspondence with all the non-dominated solutions (groups of components) contained in the archive at convergence, which identify the two-dimensional Pareto optimal surface. The results from the five different runs are aggregated.

It can be seen that case 2 achieves superior optimization results to case 1. This is an indication that the dimension of the population should be favoured with respect to the number of generations, and confirms the importance of having high genetic diversity, favoured by a larger population, to better cover the Pareto optimal front.

Table 4 reports the results aggregated from the five runs of case 2. The most DIM-important single component group is made up of component 9. Indeed, the system unavailability is most sensitive to the unavailability of this component, as it appears twice in a second-order minimal cut set (Table 2). The second most important group is made up of components 2 and 9, i.e. the first and the second most DIM-important components (Table 1). The third most important group is made up of components 2, 8, 9, i.e. the first, the second, and the third single most important components (Table 1). As a general result, the most important components of a group of a given dimension n are made up by the first n DIM-important single components: this is the

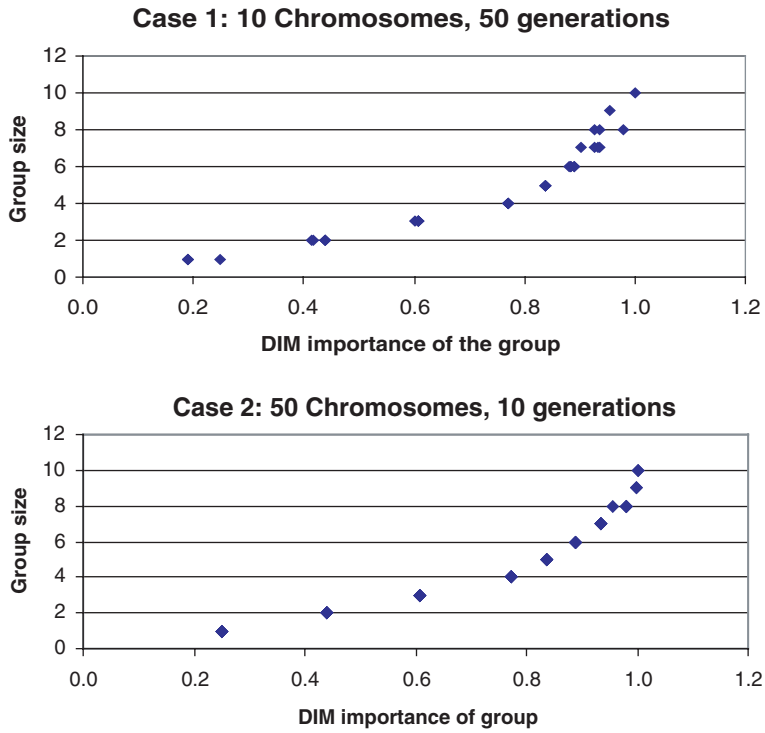

Fig. 3 Results of the multi-objective search for DIM-important groups. Two different GA evolution strategies (case 1: top, case 2: bottom). Results are aggregated for five runs

Table 4 Pareto optimal results of the multi-objective search for DIM-important groups (case 2, aggregated for the five runs)

DIM	Group size	Chromosome coding										Components
0.25	1	0	0	0	0	0	0	0	0	1	0	9
0.44	2	0	1	0	0	0	0	0	0	1	0	2, 9
0.61	3	0	1	0	0	0	0	0	1	1	0	2, 8, 9
0.77	4	0	1	0	0	0	0	0	1	1	1	2, 8, 9, 10
0.84	5	1	1	0	0	0	0	0	1	1	1	1, 2, 8, 9, 10
0.89	6	1	1	0	0	0	1	0	1	1	1	1, 2, 6, 8, 9, 10
0.94	7	1	1	0	1	0	1	0	1	1	1	1, 2, 4, 6, 8, 9, 10
0.98	8	1	1	0	1	1	1	0	1	1	1	1, 2, 4, 5, 6, 8, 9, 10
1.00	9	1	1	0	1	1	1	1	1	1	1	1, 2, 4, 5, 6, 7, 8, 9, 10
1.00	10	1	1	1	1	1	1	1	1	1	1	1, 2, 3, 4, 5, 6, 7, 8, 9, 10

obvious consequence of the additivity property of the DIM and gives proof of validation to the results of the MOGA search.

3.2 Application to the FV importance measure

The FV importance of a component is defined as the ratio of the probability of the union of all the cut sets containing that component to the system unavailability. For groups of components, it is defined as the ratio of the probability of the union of all the cut sets containing the components of the group to the system unavailability. The measure quantifies how much a single component or a group of components contributes to the system unavailability.

In this application case, the role of the GA parameters and rules was not found to be as critical as in the previous application of the DIM importance. The reason for this will be commented upon later. The rules and parameters of case 1 in Table 3 were chosen arbitrarily. Figure 4 reports the results of the search, and Table 5 reports the details of the solutions. Compared with the Pareto optimal set of the previous DIM optimization problem (Table 4), that of Fig. 4 is much reduced (i.e. three solutions compared with ten). Correspondingly, the effort by the algorithm to cover the whole set is much reduced as well. This is the reason why the actual rules and parameters of the GA matter less in this application.

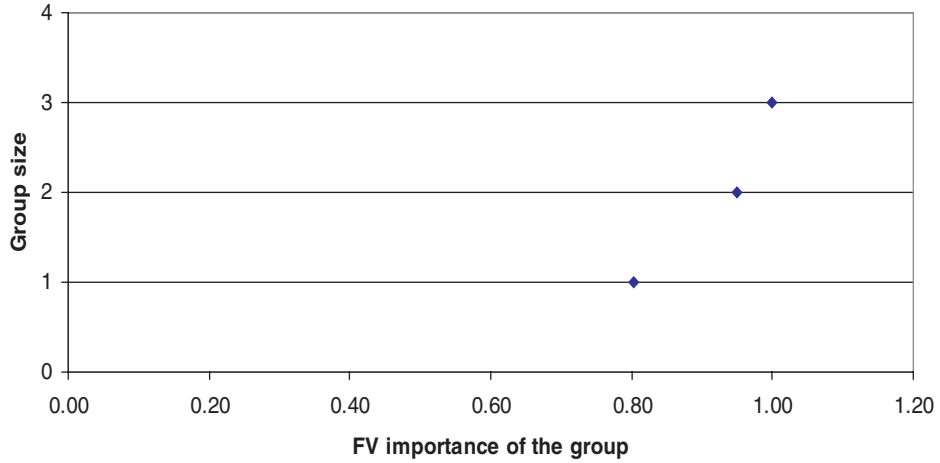

Fig. 4 Results of the multi-objective search for FV-important groups

Table 5 Pareto optimal results of the multi-objective search for FV-important groups

FV	Group size	Chromosome coding	Components
0.80	1	0 0 0 0 0 0 0 0 1 0	9
0.95	2	0 0 0 0 0 1 0 0 1 0	9, 6
1.00	3	0 1 0 0 0 1 0 0 1 0	9, 6, 2

As in the case of the DIM, the most FV-important component was found to be component 9, contributing about 80 per cent to the system unavailability. Then, components 9 and 6 contribute 95 per cent to the system unavailability and, interestingly, components 9, 6, and 2 contribute 100 per cent. This is because the triplet covers completely the set of minimal cut sets of Table 2 (i.e. each minimal cut set of the system contains at least one of the components of the triplet, so that the union of the minimal cut sets containing components of this group contribute exhaustively to the system failure). Note that in this case the importance of the group does not relate to the importance of the components taken singly, as no additivity property applies for the FV importance measure (Table 1).

3.3 Use of group IMs for prioritizing redundancy allocation

Suppose that the available budget is limited to the addition of two redundancies to two components of the system. Redundant components are of the same type (i.e. of the same unavailability) as the components they back up.

The ranking provided by the two measures FV and DIM can be used to determine for which components the redundancy is more effective in terms of reduction in the system unavailability. In particular, the DIM ranks the components based on the change in the system unavailability owing to changes in the unavailability of a component or a group of components.

Concerning the FV measure, it can equivalently be expressed as the relative reduction in the system unavailability obtainable if the component or the group of components is made perfect, i.e. with unavailability equal to zero. In this perspective, the FV measure prioritizes components, or groups of components, based on the maximal reduction achievable in system unavailability.

If the single components ranking of Table 1 was used for prioritization, then the two redundant components should be allocated as back-ups to the two most important components, i.e. components 9 and 8 according to the FV and components 9 and 2 according to the DIM.

If group importance measures were used for prioritization, then components 9 and 6 should be added a redundancy according to the FV measure of pairs of components (Table 5), or, as before, components 9 and 2 according to the DIM, which are both the highest ranked pair and the two highest ranked single components as a consequence of the additivity property of the DIM.

Table 6 reports the system unavailability values resulting from the system configuration changes suggested in the above-mentioned cases. It can be seen that the greatest reduction in the system unavailability is achieved if the two redundant components are added to components 9 and 6, the couple suggested by the FV ranking for pairs of components. This result can be explained as follows. The single components ranking cannot be used to prioritize changes on multiple components because it does not consider the effect of the interactions among the components. When one component is modified, then the system changes and the components' importance may change as well. A correct use of single components

Table 6 Impact on the system unavailability of allocating redundancy to different components

Redundancy on component	Importance measure indicator	System unavailability
None	Base case	2.70×10^{-2}
9	Single most important component for FV and DIM	8.51×10^{-3}
9, 2	Pair of most important components for DIM (coincide with the two single most DIM-important components)	7.11×10^{-3}
9, 8	Two single most FV-important components	6.66×10^{-3}
9, 6	Most FV-important pair of components	4.57×10^{-3}

IMs entails adding a redundancy to the most important component (i.e. component 9), then re-evaluating the components' importance and adding a redundancy to the most important component for the modified system. In this particular example, it was verified that when a redundancy is added to component 9, then the most FV-important component in the new system configuration becomes component 6. On the contrary, group importance measures directly incorporate the information on the components' interactions, without the need to re-evaluate the components' importance every time a modification is made.

4 CASE STUDIES 2 AND 3

The approach has been further tested on the more complex networks of Figs 5 and 6 [**9**]. All arcs have

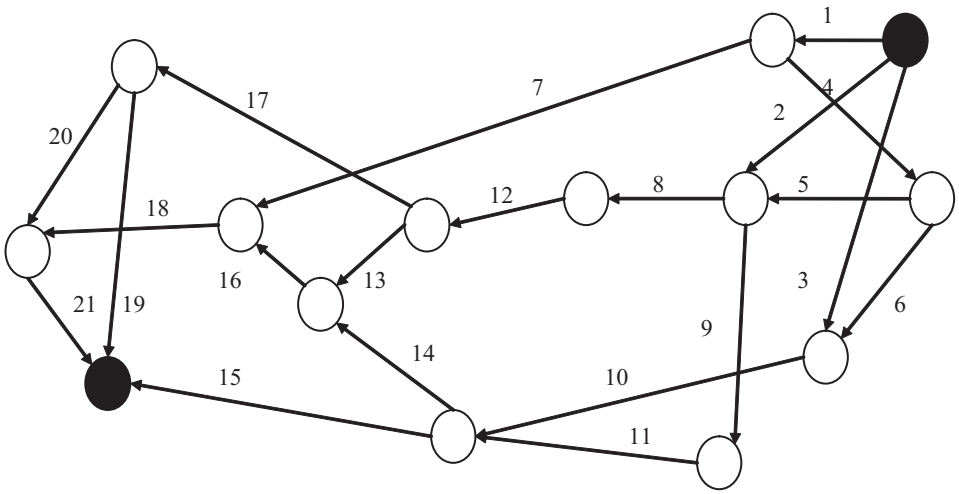

Fig. 5 Network configuration (case study 2)

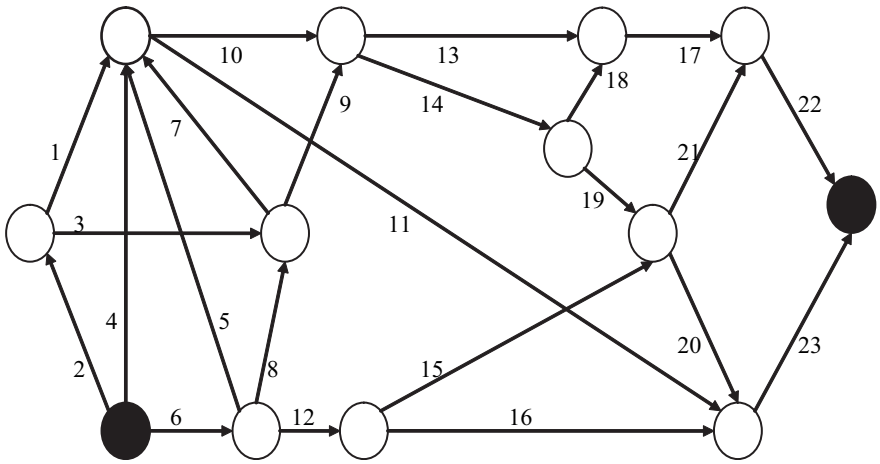

Fig. 6 Network configuration (case study 3)

unavailability of 0.1, whereas nodes are assumed perfect. The numbers of components of the two networks are 21 and 23, corresponding to $2^{21} = 2\,097\,152$ and $2^{23} = 8\,388\,608$ possible groups of components, respectively. Network 2 has 166 minimal cut sets and network 3 has 140, not reported here for the sake of brevity.

The approach has been applied with respect to the FV measure. Monte Carlo simulation is used to compute the FV of the group coded by each chromosome. GAs and Monte Carlo simulation are here efficiently coupled with the so-called drop-by-drop approach, previously introduced by one of the authors of the present paper [**17**]. The approach is based on the consideration that during the GA search, the best chromosomes appear a large number of times in the successive generations, whereas the bad solutions are readily eliminated. Thus, for each proposed

Table 7 Pareto optimal results of the multi-objective search for FV-important groups (case study 2)

FV	Group size	Components
0.62 ± 0.02	1	15
0.86 ± 0.01	2	10, 15
1.00 ± 0.00	3	3, 10, 15

Table 8 Pareto optimal results of the multi-objective search for FV-important groups (case study 3)

FV	Group size	Components
0.83 ± 0.01	1	23
0.95 ± 0.01	2	23, 6
1.00 ± 0.00	3	23, 11, 4

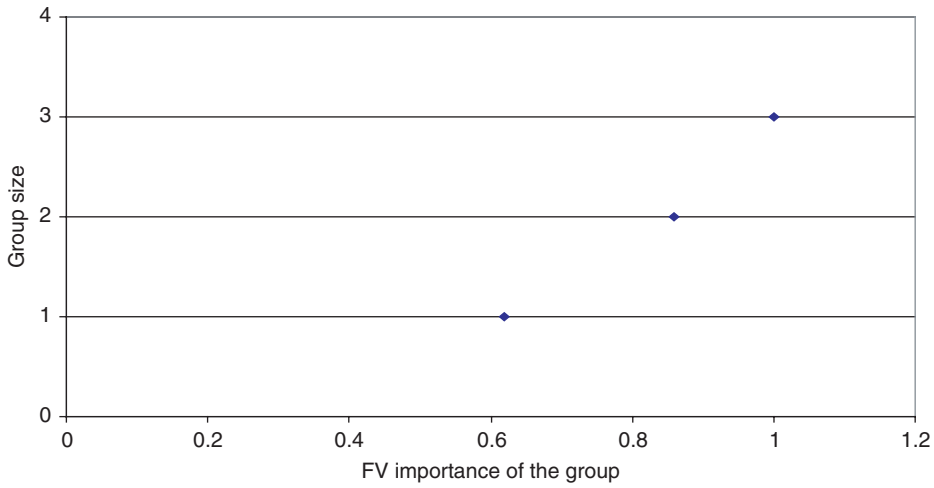

Fig. 7 Results of the multi-objective search for FV-important groups (case study 2)

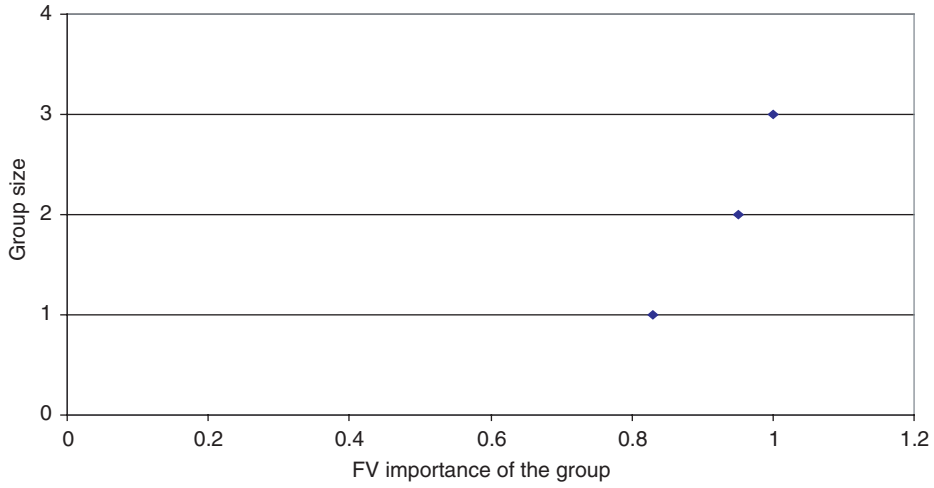

Fig. 8 Results of the multi-objective search for FV-important groups (case study 3)

chromosome, a limited number of Monte Carlo trials is run (1000, in this application). During the GA evolution, the archive of the best chromosome solutions obtained in previous Monte Carlo runs and the corresponding Monte Carlo objective functions estimates are updated. Whenever a chromosome is re-proposed, the objective functions' estimates newly computed can be accumulated with those stored in the archive, and the large number of times a 'good' chromosome is proposed by natural selection allows repeated accumulation of the results of the few-histories runs, thus ultimately achieving statistically significant results.

The results of the GA searches and the details of the Pareto optimal solutions found are reported in Tables 7 and 8, and Figs 7 and 8. The results are similar to those obtained for network 1: three groups are identified, from the most important single component to the most important triplet. Again, the reason why the triplet contributes 100 per cent to the unavailability (i.e. $FV = 1$) is that it covers all minimal cut sets of the network. This was verified by inspection of the minimal cut sets. An interesting property of the smallest group with $FV = 1$ is that it represents the highest availability path from source to terminal.

5 CONCLUSIONS

In this paper, the feasibility of using GAs to search for the most important groups of events or components in a complex system has been investigated. The problem is framed as a multi-objective search, where the decision variables are the groups of events and the objectives are the maximization of the importance of the groups and the minimization of their dimension.

A GA approach has been undertaken. A first application concerned a network system of literature and the identification of groups of components that are important with respect to two importance measures, the DIM and the FV importance measure, with reference to the effects of components' failures on system unavailability. In both cases, the approach was able to identify the most important single events, couples of events, triplets, and so forth. Successively, the approach has been applied to two more complex network systems, with satisfactory performance.

The application of group importance measures has been discussed in connection with the prioritization of redundancy allocation for optimal system configuration, under limited budget. It has been shown that prioritization based on single components' importance measures may lead to sub-optimal results, thus supporting the use of group importance measures.

Future work will be devoted to the application of the approach to larger-scale systems in which nodes can also fail and the improvement of the GA evolution strategy to cover fully the Pareto optimal set (e.g. by inducing evolutionary niches). Potential applications of the approach include support to risk-informed decision making for nuclear power plants. Indeed, changes in the technical specifications (surveillance and/or test frequencies, etc.) may very well impact groups of components. The approach could also be used to find groups of components that can be tested simultaneously, minimizing the impact on the safety of the outage of multiple components. Another application could be the identification of critical states for the nuclear power plant that must be avoided, as per the limiting conditions for operations. Future work needs to explore the above application cases, in order to derive guidance on the appropriate importance and performance measures, as well as on how to inform decision making from the results.

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