The Alarm Processing for Power Networks Benchmark

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Version 1 (August 2011)

The APPN domain is an encoding of a discrete event system (DES) diagnosis problem as a planning problem [2]. The aim of diagnosis, in the context of alarm processing, is to find an explanation of the observed alarms, which is a possible execution of the system that generates the same set of observations, with a minimum number of "unexplained" events. In the encoding as a planning problem, actions that correspond to unexplained events have a cost of 1, while other actions have a cost of 0, so the objective is to find a plan of minimum cost.

The diagnostic model is highly simplified: for instance, it does not accurately model the propagation of electricity through the network. In spite of this, it is sufficient to generate meaningful explanations of some real alarm logs [1].

Domain Formulations

There are three domain formulations: Classical, Timed-TIL and Timed-NoTIL. Note that all formulations encode the same problem: in particular, *the objective in all formulations is to minimise the sum of action costs.* The difference between the formulations is only in how some constraints on valid plans are expressed.

All formulations use some quantified conditional effects, but these are conditioned only on static predicates. A plain STRIPS version of each formulation (using one domain file per instance) is also provided. The two timed formulations differ in that one uses timed initial literals and the other does not.

Problem Instances

The problem instances in this domain are randomly generated, but in a way aimed to make them "similar" to real problem instances. This was done by building a statistical model of the distribution of and associations between types of alarms in the original data, and generating problems according to this model. The result is reasonable, but not perfect. The random instances are somewhat less structured. Figure 1 shows the distribution of the estimated ratio of explicable alarms in the real and randomly generated data. (This ratio, for an instance, is $\frac{A-c^\star}{A}$, were A is the number of alarms and $c^\star$ is the minimum solution cost, i.e., the minimum number of unexplained alarms; it is an estimate because a lower bound on $c^\star$ is used when the true minimum is not known.) In the real data, there is a large number of instances in which no alarm can be explained, but a small set of instances that allow a high fraction of explained alarms. Among the random instances, on the other hand, there is a much larger number where a small fraction of alarms is explicable, but instances with a really high fraction of explained alarms are rarer.

Instances with a zero ratio of explicable alarms are not particularly interesting as benchmark problems, since the trivial solution is optimal. Therefore, 35 instances where selected (from 600 instances generated with some variation in parameters) only among those with a ratio of at least 0.2. Table 1 summarises characteristics of the chosen instances: #O and #C are the number of observations and components, respectively. #A is the number of alarms (observations that are not commands or command responses). This is an upper bound on plan cost, i.e., there always exists a plan with cost less than or equal to #A. The last columns are all lower bounds on cost: the value of the LM-Cut heuristic in the initial state, the highest f-value proven by an A* search with this heuristic within 1 hour CPU time and 3Gb memory limits, and the value computed by the h^{++} lower bound function, also within 1 hour CPU time and 3Gb memory limits. A $\star$ on any lower bound indicates that a matching plan was found, i.e., the bound is in fact the optimal plan cost.

The lower bounds in the table were obtained from the classical formulation (since no effective optimal planner or lower bound function exists for the timed formulations). However, the bounds should be valid for all formulations. A few examples of optimal plans (written by hand) are provided for the timed formulations.

References

[1] A. Bauer, A. Botea, A. Grastien, P. Haslum, and J. Rintanen. Alarm processing with model-based diagnosis of discrete event systems. In *Proc. 22nd International Workshop on Principles of Diagnosis (DX'11)*, 2011. To appear.

[2] P. Haslum and A. Grastien. Diagnosis as planning: Two case studies. In *ICAPS'11 Scheduling and Planning Applications Workshop*, 2011.

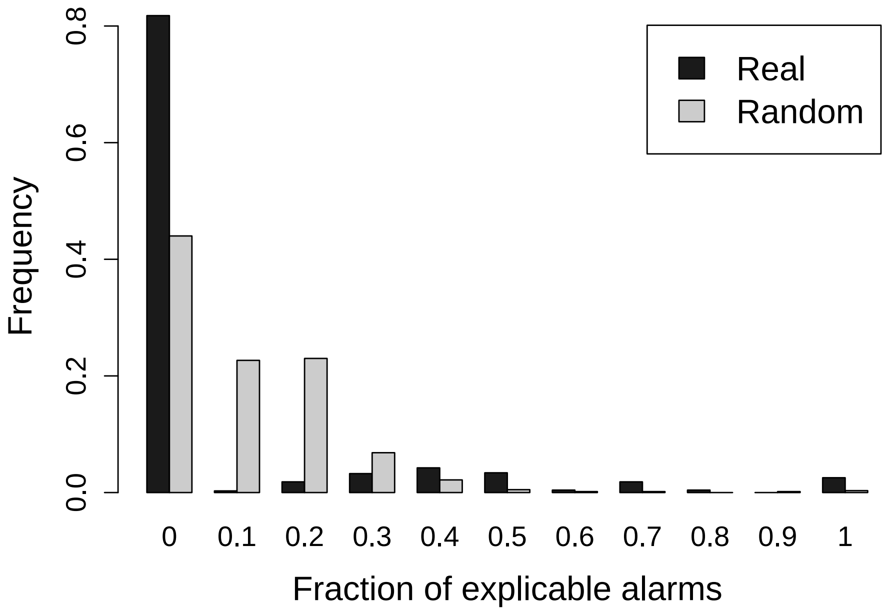

Figure 1: Distribution of the estimated ratio of explicable alarms in real and randomly generated data.

	#O	#C	#A	$h(s_0)$	A*	h^{++}
test01-S3-83	5	1	3	2	2$\star$	2$\star$
test02-S2-46	7	5	4	2	2$\star$	2$\star$
test03-S3-88	5	6	3	1	1$\star$	1$\star$
test04-S2-30	5	8	5	4	4$\star$	4$\star$
test05-S3-134	7	10	4	3	3$\star$	3$\star$
test06-S2-4	5	11	2	0	0$\star$	0$\star$
test07-S2-169	6	14	3	2	2$\star$	2$\star$
test08-S2-40	20	19	14	11	11$\star$	11$\star$
test09-S3-4	6	20	4	2	2$\star$	2$\star$
test10-S2-99	20	21	9	7	7$\star$	7$\star$
test11-S3-165	20	26	20	14	14	14$\star$
test12-S2-163	14	28	6	3	4$\star$	4$\star$
test13-S2-47	20	28	13	10	10	10$\star$
test14-S2-178	20	31	20	13	13	14
test15-S2-72	20	31	20	16	16	16
test16-S2-25	20	33	19	14	14$\star$	14$\star$
test17-S3-64	20	35	14	9	9	11$\star$
test18-S2-71	20	38	20	15	15$\star$	15$\star$
test19-S2-177	20	41	18	11	11	12$\star$
test20-S3-90	20	44	17	12	12	13$\star$
test21-S4-175	60	45	54	42	42	43
test22-S2-185	20	47	15	12	12	12$\star$
test23-S3-145	20	51	20	16	16	16$\star$
test24-S3-159	20	52	20	14	14	14$\star$
test25-S3-80	20	54	20	15	15	15$\star$
test26-S4-4	60	66	58	44	44	44$\star$
test27-S4-33	60	86	60	46	46	48$\star$
test28-S4-63	60	96	60	43	43	44$\star$
test29-S4-38	60	101	56	40	40	41$\star$
test30-S4-178	60	108	60	48	48	48$\star$
test31-S4-191	60	114	56	39	39	41$\star$
test32-S4-196	60	114	57	39	39	40
test33-S4-10	60	131	58	44	44	45$\star$
test34-S4-156	60	131	60	38	38	40
test35-S4-8	60	142	56	43	43	44$\star$

Table 1: Size and bounds on plan cost for the selected instances.