Automated Mapping of Business Process Execution Language to Diagnostics Models

Hamza Ghandorh[1] and Hanan Lutfiyya[2]

[1]Department of Electrical and Computer Engineering, Western University, London, Ontario, Canada

[2]Department of Computer Science, Western University, London, Ontario, Canada

Keywords: Web Service Composition Diagnosis, Codebook Technique, BPMN Mapping.

Abstract: This paper illustrates how a specification of a business process can be automatically mapped to a fault diagnostic model. Observed failures at run-time are quickly analyzied through the diagnostic model to determine the faulty service.

1 INTRODUCTION

Web services are loosely-coupled, self-contained, and self-describing modules that perform a predetermined task. Services can be used in multiple applications and thus are reusable. A service of a particular type can be replaced by another service if necessary. The architectural paradigm for organizing distributed applications based on a composition of web services, which may be under different ownership, is referred to as a Service-Oriented Architecture (SOA) (Papazoglou and Van Den Heuvel, 2007) . These compositions can be used to implement a business processes (Lins et al., 2012).

A *fault* (Garza et al., 2007, Alam, 2009) is a defect in either hardware or software that causes a failure. A failure occurs when a service deviates from expected behaviour. To illustrate the relationship between fault and failure consider the following example. A hardware power loss causes a service to become unavailable. The cause of the hardware power loss is the fault and the failure is that the service has become unavailable. In another example an unexpected load may result in a service provider in not providing a response in the expected time i.e., a Quality of Service (QoS) requirement may be violated. The cause of the unexpected load is the fault and the failure is the violation of the QoS requirement.

A fault (or problem) may cause multiple failures (often referred to as *symptoms*). For example, a composition of services could have service WS_i that communicates with WS_j and WS_j communicates with WS_k. If WS_k becomes unavailable then WS_j may not be able to complete a request from WS_i and thus WS_i observes a failure of WS_j. Another example can be seen in a composition which consists of services WS_i, WS_j, WS_k and WS_l. The first three of these services are clients of WS_l. If the machine that WS_l is hosted on goes down (and thus WS_l is not available) then the other services observe a failure of WS_l. *Fault diagnosis* is used to determine a fault and often includes analysis of notifications of failures (referred to as *events*).

To provide a robust service experience, it is important to have an effective and efficient mechanism for fault diagnosis (Zhang et al., 2012*a*). Model-based fault diagnosis performs fault diagnosis through models. Some of these, e.g., codebook, have been shown to be effective in practice. Many fault diagnosis models require knowledge of the application configuration. With the sheer number of possible applications there is a need to automate the development of a fault diagnosis model.

This paper proposes an approach to the generation of a fault diagnosis model based on a notational representation of a business process. We show the fault diagnosis model can be used in the management of service compositions.

This paper is organized as follows: Section 2 provides the background, Section 3 presents related work on fault diagnosis, Section 4 presents the proposed approach. Section 5 describes the architecture of management system for a diagnostic module that uses our approach, Section 6 describes the results of the testing of our implementation, and Section 7 concludes the paper.

Ghandorh H. and Lutfiyya H..
Automated Mapping of Business Process Execution Language to Diagnostics Models.
DOI: 10.5220/0005430702510259
In *Proceedings of the 5th International Conference on Cloud Computing and Services Science* (CLOSER-2015), pages 251-259
ISBN: 978-989-758-104-5

2 BACKGROUND

This section describes fault diagnosis and a notation for describing a business process.

2.1 Fault Diagnosis

The process of fault diagnosis requires the following: *fault detection*, *fault localization*, and *testing* (Steinder and Sethi, 2004). Fault detection is the process of capturing symptoms (Hanemann, 2007). Detection techniques can be based on active schemes (e.g, polling to determine availability) and/or symptom-based schemes, where a system component indicates that it has detected a failure. Examples of proposed fault detection techniques can be found in Angeli et al (Angeli and Chatzinikolaou, 2004) and Hwang et al (Hwang et al., 2010).

Fault localization typically requires an analysis of a set of observed symptoms. The goal of fault localization is to find an explanation of the symptoms' occurrence. The explanations are delivered in the form of hypotheses. Hypotheses are statements which explain that each observed symptom is caused by one or more designated problems. Based on these hypotheses, a testing step is performed in order to determine the actual problems through the application of a suitable testing mechanism (Steinder and Sethi, 2004).

There are several fault localization techniques techniques. One of these, *event correlation*, attempts to associate one symptom with another symptom in order to infer the relationship between their occurrences (Tiffany, 2002). Through an examination of these associations, a number of possible hypotheses are generated that reflect the symptoms' occurrence. There are several different types of correlations, which are useful for diagnosing problems in a network. One of these is described in 3.

In this work when we say that we are mapping a business process specification to a fault diagnosis model we are specifically referring to a model that supports fault localization.

2.2 BPMN

One standard that can be used to model business processes is referred to as Business Process Modeling Notation (BPMN)(Alonso et al., 2004) (Endert et al., 2007). BPMN has several notational elements. An activity node represents a web service. A link represents different possible flows and is chosen based on the result of the evaluation of a condition of an activity. A gateway represents decision points that represent a workflow's conditions. A sequenceflow represents a link from a gateway node to an activity node. A pool represents the combination of a composition of flowobjects, gateways, and sequenceflows. A messageflow describes the exchange of messages between pools, and an event describes the start or end point of workflow. A pool may have an activity flowobject that can be represented by another pool. Each pool represents a workflow and a business process is associated with a set of pools. An example of a business processes workflow modelled as a BPMN specification is presented in Figure 1.

3 RELATED WORK

Steinder et al. (Steinder and Sethi, 2004) proposed a classification of fault localization techniques which is derived from graph-theoretic techniques and included techniques such as codebook, context-free grammar, and bipartite causality approaches. Graph-theoretic techniques rely on the use of graphs. The graphs include nodes that represent symptoms and problems, while directed edges are used to model the relationship between the problems and symptoms. Essentially edges represent cause-effect relationships between problems and symptoms or symptoms and other symptoms. An example is seen in Figure 3(a). To create such a model, an accurate knowledge of current dependencies among the system components is required. The rest of this section briefly describes representative work on fault diagnosis based on the relationships between problems and symptoms.

Tighe et al. (Tighe and Bauer, 2010) implemented a distributed fault diagnosis algorithm, proposed by Peng and Reggia and is referred to as *Parsimonious Covering Theory* (Peng and Reggia, 1990), in a policy-based management tool called BEAT (Best Effort Autonomic Tool) (Bahati et al., 2007). The algorithm is concerned with the generation of plausible hypotheses or *covers*, based on given information that comes from graph-theoretic models, prior to diagnosis. Hypotheses are delivered and grouped in order to generate disorder-and-manifestation statements that are forwarded to a decision making system for recovery actions.

Zhang et al. (Zhang et al., 2012*b*) proposed a hybrid diagnosis method to diagnose web services' problems in service-oriented architectures. Their method combines dependency matrix-based diagnosis and a Bayesian network-based diagnosis. Although the authors considered the reduction of the computational complexity of services diagnosis, the hybrid diagnosis method does not cope with the dynamic nature of SOA's services, and Bayesian net-

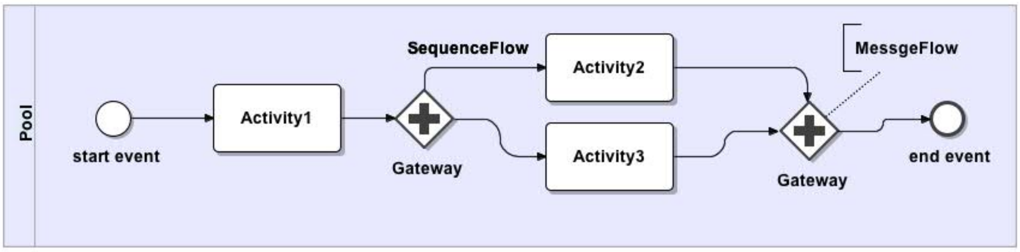


Figure 1: Simple BPMN example.

work diagnosis provides slow measurement.

Ardissono et al. (Ardissono et al., n.d.) proposed a model-based diagnostic framework with autonomous diagnostic capabilities to monitor the state of web services. As a partially distributed approach, the framework includes several local diagnosers, which is attached to a web service or a composition, cooperate with a global diagnostic service. As soon as local diagnosers notice a problem, they raise an alarm to the global diagnostic service to detect it.

Most of the above work focuses on the models. None of the work investigated shows how to automate the development of a fault diagnosis model based on a specification of a business process. However, there is work (e.g., (Morán et al., 2011)) that takes a business process specification and maps it to control rules.

4 PROPOSED APPROACH

This section describes our approach to using the BPMN specification of a business process to a fault diagnosis model.

4.1 Codebook Technique

Earlier we discussed that a fault may manifest itself in the unexpected behaviour of a web service that is observed by other web services. For our our fault diagnosis model we use a fault propagation model, which describes which symptoms that may be observed if a specific fault occurs (Kätker and Paterok, 1997). The underlying mathematical structure is typically a graph (Steinder and Sethi, 2004). For this work we chose the codebook technique (Kliger et al., 1995). This technique was implemented in a network fault diagnostic system and the results (Yemini et al., 1996) suggest that this approach is highly scalable.

The codebook technique or coding technique (Steinder and Sethi, 2004) uses a causality graph and problem code (PC) matrix of a web service composition's workflow to locate the source of failures. A causality graph is a bipartite graph whose vertices can be partitioned into two disjoint subsets V and W such that each edge connects a vertex from V to one from W (Caldwell, 1995). A PC matrix is a matrix representation of a causality graph used to infer the causes of observed symptoms. The PC matrix is built based on the causality graph. An example of the causality graph and the matrix are illustrated in Figure 3(a) and 3(b), respectively. The matrix consists of a column that represents symptoms that problems cause. A matrix entry either has the value of zero or one. For example, the value of one assigned at $PC[1,1]$ position in PC matrix indicates that symptom S_1 can be observed for problem P_1. The value of zero assigned at $PC[1,3]$ position indicates that symptom S_1 can not be observed for problem P_3.

At run-time a problem will cause one or more symptoms to be generated. From this a string can be formulated. If the i^{th} symptom was observed then the i^{th} position in the string is one otherwise it is zero. This string will be referred to as a *current symptoms vector* (CSV).

The diagnosis process uses the *Hamming distance*. The Hamming distance is the minimum number of substitutions that transforms one string into the another. For example, the Hamming distance between two words "toned" and "roses" is three letters and the Hamming distance between the two strings 1011101 and 1001001 is two bits (MacKay, 2005). Each value in a column in the PC matrix is compared with its corresponding code in a given CSV. If both values are identical (i.e, the value in the column in the PC matrix and its corresponding code in the given CSV are the same), the Hamming distance value is denoted as zero. Otherwise, the Hamming distance is denoted as one. The values are then summed to determine the Hamming distance of the two words. The minimum of the Hamming distance values is an indicator of the corresponding problems as the causative problems. For the PC matrix, if the given CSV is 11000, the Hamming distance is (0,4,4) for columns labeled P_1,P_2 and P_3 respectively. Thus, the causative problem was P_1. If the given CSV is 11101, the Hamming distance is (2,2,4) for columns labeled P_1, P_2 and P_3 . Thus, the causative problems are limited to P_1 and P_2.

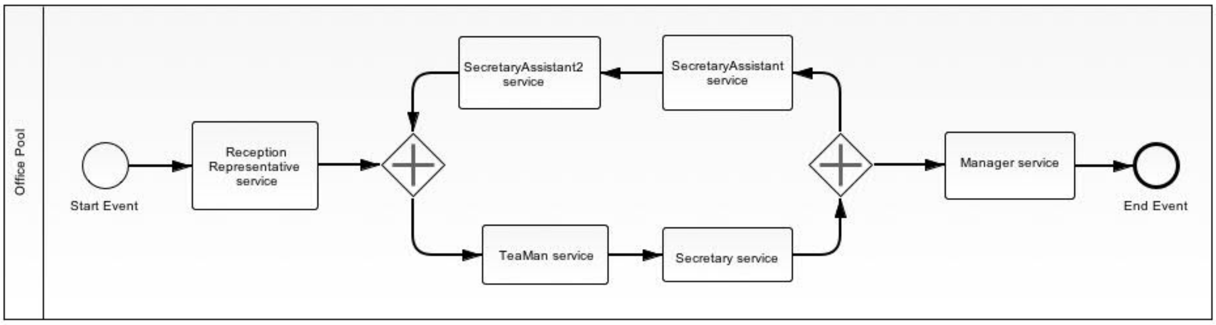
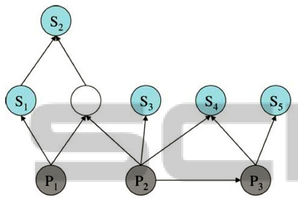


Figure 2: Office Business Process BPMN.



(a) Causality Graph

	P_1	P_2	P_3
S_1	1	0	0
S_2	1	1	0
S_3	0	1	0
S_4	0	1	1
S_5	0	1	1

(b) PC matrix

Figure 3: Example of causality graph and PC matrix (Steinder and Sethi, 2004).

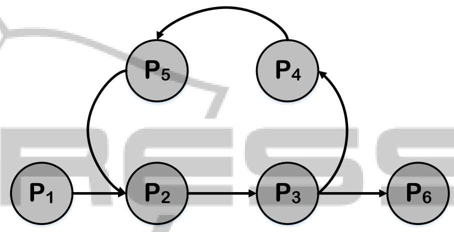


Figure 4: Abstract View of Office Business Process.

4.2 BPMN Mapping

The BPMN mapping is done through the transformation from BPMN graphs to a composition dependency (CD) graph which is done prior to determining the causality graph. For illustration purposes, Figure 2 presents BPMN model for a office business process, which is concerned with delivering only important mails to the manager office through different filters. The transformation from BPMN to a CD graph is performed as follows: assume that a CD graph is represented as (V,E). Each BPMN atomic activity node is a node in V. If a decision point follows an activity then the node in V representing the activity will have two outgoing edges. Edges represent different possible flows. Figure 4 depicts the CD graph for the office business process, where P_1 represents the Reception-Representative service, P_2 represents the TeaMan service, P_3 represents the Secretary service,P_4 represents the SecretaryAssistant service, P_5 represents the SecretaryAssistant2 service and P_6 represents the Manager service. We note that the granularity of the model is limited to a service. Hence a problem, P_i, corresponds to a service. We will use the notation P_i to refer to both a problem and to a service.

Assume that the CD graph is represented as (V,E) while the causality graph is represented as (V',E')[1]. The set V' can be partitioned into two sets W,X such that each edge in E' connects a vertex from W to a vertex in X. The set W is the set of potential problems. Since each node in the CD graph represents an activity and any of these activities can be faulty then the set of W is the same as the set V. Let v be a node in a CD graph. This node represents a potential problem. Any node, u, in the CD graph, for which there exists a path from it to the node v, potentially could exhibit a failure condition if v becomes faulty. Any node that could exhibit a failure condition is in set X. For a node u we use the notation P_u to represent u as a problem and S_u to represent u as a symptom. Determining the causality graph of the CD graph requires these two algorithms: *Modified Deph-first Search* (mdfs), and *pathGenerator*. The mdfs and pathGenerator algorithms are presented in algorithm 1 and algorithm 2, respectively. The mdfs algorithm takes as input a CD graph and does a depth-first traversal. When all child nodes of node v have been traversed then the pathGenerator algorithm is used to generate all paths from node v to each leaf node. These paths are used to produce the causality graph. The causality graph of the office business process is depicted in Figure 5.

The mdfs algorithm uses two variables: *VerticesList*, and *BackTrackEdgesList*. VerticesList is a list that keeps track of each node's label. The BackTrackEdgesList maintains a list of backtrack edges. A backtrack edge (v,w) indicates that the mdfs algo-

[1]The causality graph vertices are known in advance based on the given information from a client about fault and symptom quantities

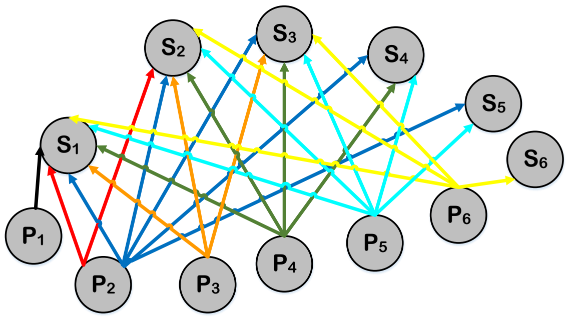


Figure 5: Causality graph of the office business process.

rithm is revisiting node w and that not all of node w's children had yet been visited. *White* is a label that indicates an unvisited node, which is the initial state for all nodes. *Gray* is a label that indicates a node has been visited but not all of its children have been traversed. *Black* is a label that indicates a node has been visited and all of its children have been processed. When the input CD graph is received, mdfs is triggered (line 1). If the current node being visited is White, mdfs will assign the Gray label (line 3). The mdfs algorithm examines each outgoing edge (lines 4-5). If the node on the other end of the edge is labelled White then this means that the node has not been visited and thus no paths have been generated (lines 6-7). If the node on the other end of the edge is labelled Gray then the edge is put in the BackTrackEdgesList (lines 8-9). If there is no unvisited neighbour node for the current node, mdfs executes the pathGenerator algorithm in order to generate paths (line 12).

The pathGenerator algorithm is executed when all nodes on the other end of the outgoing edges of node v have been visited. The pathGenerator uses three variables: `newPath`, `pathsW`, and `Paths`. The `newPath` variable is used to represent a sequence of nodes, and `pathsW` represents a set that contains all the paths from w to all leaf nodes. `Paths` is a container for all possible paths. The pathGenerator algorithm is executed when a current node v is received from mdfs. The pathGenerator looks for outgoing edges of node v. If there are no outgoing edges (line 2), the pathGenerator algorithm creates a new path, appends v node in this path, and adds the path to `Paths` (lines 5-7). If there are one or many outgoing edges (line 8), the pathGenerator algorithm retrieves each path associated with w and creates a new path by putting together v and the path associated with w (lines 10-19).

The execution of the algorithms does not always provide all paths. This happens where there is a cycle. The existence of backtrack edges indicate a cycle. Assume a backtrack edge: (v,w). The mdfs algorithm will generate all paths from node w to leaf nodes but the paths generated for node v will not include those paths that start at w. For example, the edge (P_5,P_2) is a backtrack edge in Figure 4. The paths from the root node (P_1) to all nodes in the office CD graph are: $((P_1), (P_1,P_2), (P_1,P_2,P_3), (P_1,P_2,P_3,P_6), (P_1,P_2,P_3,P_4), (P_1,P_2,P_3,P_4,P_5))$. After considering the backtrack edge (P_5,P_2), the paths will be: $((P_1), (P_1,P_2), (P_1,P_2,P_3), (P_1,P_2,P_3,P_6), (P_1,P_2,P_3,P_4), (P_1,P_2,P_3,P_4,P_5), (P_1,P_2,P_3,P_4,P_5,P_2))$. Paths generated considering backtrack edges are done after mdfs terminates. Let (v,w) be a backtrack node. Let P be the set of paths. For each path that ends with w create a new path that appends v to the path that ends with w.

Algorithm 1: Modified depth-first search(mdfs).

Procedure: mdfs executed on receipt Graph G with root node v

Input : $G = (V,E)$ where $E = \{(v,w) \mid v,w \in V\}$ and node v is a zero indegree edge and all nodes v are initially unvisited.

Variables : VerticesList carrys on all nodes, White is label for unvisited node state, Gray is label for the visited but not finished node state. Black is label for the finished node state. BackTrackEdgesList carrys on edges resulted from visiting Gray nodes.

```
1  mdfs(G,v)
2  if VerticesList[v] = White then
3      VerticesList[v] = Gray
4      forall the e ∈ G.incidentEdges(v) do
5          w = G.incidentEdges(v,e)
6          if VerticesList[w] = White then
7              mdfs(G,w)
8          else if VerticesList[v] =Gray then
9              putEdge(v,w,BackTrackEdgesList)
10     VerticesList[v] = Black
11     // when there are zero unvisited
       nodes, backtrack
12     pathGenerator(v)
```

4.3 Diagnostic Models

The Codebook technique (Steinder and Sethi, 2004) is used as our diagnostic model. Each path generated starts from a node v and ends at a node w. If a problem occurs in node w then it is possible that symptoms are detected by each node in the path. Thus each path generated is represented in PC matrix as a column. We see this with Figure 5 and Table 1.

Algorithm 2: pathGenerator.

```
Procedure: pathGenerator executed on receipt
           a graph G and node v
Input    : Graph G and node v from mdfs
Variables : newPath, pathsW, and Paths
Output   : Possible set of paths
begin
    if G.incidentEdges(v) == null then
        // Create a new path, add v
        node in this path, and add the
        path to Paths
        newPath = null
        newPath.append(v)
        Paths = Paths ∪ newPath
    else
        forall the e ∈ G.incidentEdges(v) do
            w = G.incidentEdges(v,e)
            pathsW = emptySet
            // Retrieve all previously
            generated paths from w to
            each leaf node reachable
            from w
            forall the p ∈ Paths.get(w) do
                newPath = null
                newPath.append(v)
                newPath.append(p)
                pathsW.add(p)
            Paths = Paths ∪ pathsW
```

Table 1: Problem codes matrix for the office business process.

	P_1	P_{2_1}	P_{2_2}	P_3	P_4	P_5	P_6
$S1$	1	1	1	1	1	1	1
$S2$	0	1	1	1	1	1	1
$S3$	0	0	1	1	1	1	1
$S4$	0	0	1	0	1	1	0
$S5$	0	0	1	0	0	1	0
$S6$	0	0	0	0	0	0	1

By apply the mdfs and pathGenerator algorithms on the office CD graph, in Figure 5, since $S4$ can be observed for P_4, the $\texttt{PC}[4,4]$ is assigned the value of one. Since symptom $S5$ can not be observed for P_6, $\texttt{PC}[5,6]$ has been assigned the value 0. All codes assigned to present the causality relationships in Figure 5 are portrayed in table 1. In table 1, there are two columns representing different patterns that result in symptoms associated with the web service that is associated with problem P_2. These are represented by (P_{2_1}, P_{2_2}).

Fault diagnosis assumes a vector of symptoms that have been reported. It is assumed that these symptoms are generated by a failure detection component located within a composition. The Hamming distance between the vector and each column is calculated. The lower the value of the Hamming distance the more likely that the column explains what is causing the symptoms.

For the office business process assume that the following symptoms are observed: P_1 says that P_2 has timed out, P_2 says that P_3 has timed out, P_3 says that P_4 has timed out, and P_4 says that P_5 has timed out, and P_5 says that P_6 is not responding. For this pattern of symptoms, the `CSV` is 111110. Based on the `PC matrix` for the office business process, the result list is depicted at Table 2. From Table 2, the causative web service for the observed symptoms are P_2 and P_5 since they have the minimum values between their peers.

Table 2: Result list of the office business process.

	P_1	P_{2_1}	P_{2_2}	P_3	P_4	P_5	P_6
$S1$	0	0	0	0	0	0	0
$S2$	1	0	0	0	0	0	0
$S3$	1	1	0	0	0	0	0
$S4$	1	1	0	1	0	0	1
$S5$	1	1	0	1	1	0	1
$S6$	0	0	0	0	0	0	1
$\sum$	4	3	**0**	2	1	**0**	3

5 ARCHITECTURE

Section 4 presents an approach to automating the development of a fault diagnostic model. This model is part of the diagnosis module of a third party third party policy-based management system (Hasan, 2011). The management system allows for Service-Level Agreements (SLAs) to be negotiated. These SLAs formalize the QoS requirements. Policies are used for three types of decisions: *service selection*, *SLA violation* and *recovery* policies (Hasan, 2011). The service selection policy is defined by clients to guide choice of services. The violation policy specifies what constitutes a violation of an SLA. The recovery policy is defined by clients that specifies recovery actions to be taken when the management system detects a SLA violation.

5.1 TPA

A key component in the management system is the third party agent (TPA). The TPA carries out these tasks: (1) allows all clients, providers, and provided services to be registered with it; (2) negotiates SLAs, polices, and keeps track of violated SLAs; (3) generates events to indicate failures and performs recovery actions. An overview of the TPA is presented as Figure 6. The Registration Gate is responsible for (1) forwarding a business process specification to the BPMN Repository, which stores the BPMN specification for each composition being managed by the TPA. This is one of the inputs for the Diagnosis Module. (2) forwarding relevant information about clients and providers to the Negotiator. The Negotiator is responsible for maintaining an agreement (i.e. SLA) between a client and a service provider if both parties have a match between the former's needs and the latter's specification. These agreements are stored in the Contract Repository. The Event Generator relies on the stored information found in logs storage, such as, information related to service invocations. The Event Generator also "uses SLAs and SLA violation policies to generate events that represent SLA violations ... when the number [SLA violations] exceeds what is specified in the SLA violation policy then an event is generated"(Hasan, 2011). The diagnosis module receives the generated events and uses the generated diagnosic model to deliver a diagnostic hypotheses. The Recovery Agent is responsible for analysing the diagnosis module's hypotheses and executing reactive actions.

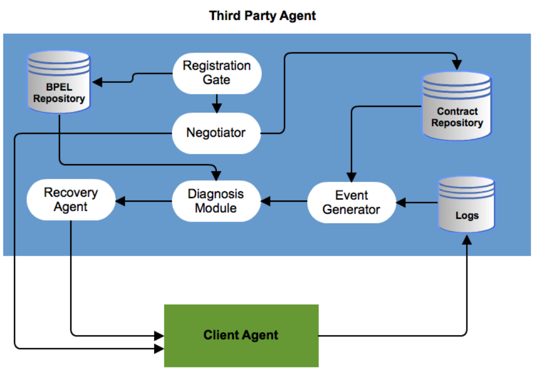


Figure 6: TPA with the Client Agent.

5.2 Diagnosis Module Overview

Our proposed diagnosis module provides a hypothesis about the source of symptoms observed in a composition. The basic module architecture is presented in Figure 7. There are main three components: (1) The Mapper which transforms received BPMN specifications to PC matrix; (2) The Event Coordinator which transforms the generated events to CSV; (3) The Matcher which is responsible for matching PC matrix and CSV to deliver a hypothesis to the Recovery Agent. The Mapper is only used for new applications or if an application is modified. Otherwise at run-time only the Event Coordinator and Matcher are used. We note that our model narrows the problem to a service. Further tests could be carried out to further narrow down the root cause. However, for recovery purposes it may be sufficient to know the service that is causing failures and the action could be to select another instance of the same type.

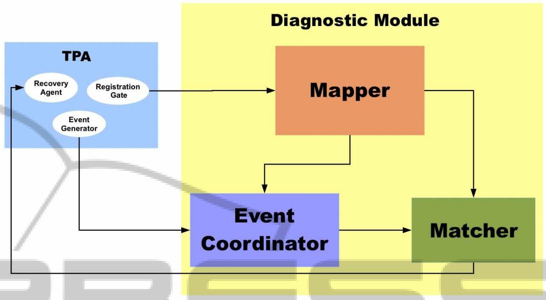


Figure 7: Diagnosis module with the TPA.

6 EVALUATION

After we implemented the Mapper, the Event Coordinator, and the Matcher components, we tested our diagnosis module on composition description graphs to see if the module is able to accurately and correctly determine the source of events. We ran the diagnosis module on a single machine with 2.66 GHz Intel Core 2 Duo processor, Mac OS X 10.6.8 , and eight gigabyte 1.07 GHz memory. We used Netbeans 7.0.1 IDE to run tests and create or manipulate CSVs. For the transformation from BPMN to the composition description graphs, we used a tool referred to as the BPMN Modeler, which is an extension of eclipse IDE (Eclipse, 2011). The BPMN Modeler is responsible for creating a BPMN for a business process and forwarding a BPMN textual description to the Mapper component.

We applied our diagnosis module to nine subjects which consists of: single or many joins (i.e. single or many vertices' edges ending in one vertex), single or many splits (i.e. single or many vertices' edges starting from one vertex and ending at an other vertex), single or many cycles (i.e. single or many vertices' edges starting and ending at the same vertex), self cycles (i.e. single vertex' edges is starting and ending at the same vertex), and trees (i.e. single or more vertices are interconnected in a hierarchical manner). For each performed test, we assumed that one fault could happen for each subject. For each subject we did a test for each web service going down. All evaluation results and specifications and execu-

Table 3: Nine CD graphs specifications.

No	CD Graph	Vertices Number	Edges Number	Single Cycle	Self Cycle	Many Cycles	Single Split	Many Splits	Single Join	Many Joins	Diagnosis Time [4]	Execution Time [5]
1	Office CD	6	6	•			•		•		3.2	1.68
2	CD 1	7	9		•	•					5.8	1.85
3	CD 2	6	6	•							2	1.65
4	CD 3	10	10					•	•		13.2	2.24
5	CD 4	11	12					•		•	9	2.30
6	CD 5	16	20					•		•	32.8	5.87
7	CD 6	100	114			•		•		•	328.8	16.16
8	CD 7	9	11					•		•	9.4	1.93
9	CD 8	33	34	•				•	•		32.8	5.43

[4] Time measured in milliseconds
[5] Time measured in seconds

tion time of composition dependencies graphs are presented in table 3. A correct diagnosis was found 100% of the time. In cyclic composition description graphs, the diagnosis module indicates not only the problematic node but also the closest predecessor node to the causative node. The reason is that both the causative node and the predecessor node have the same code in the PC matrix. Thus, any faults occurring in either these nodes will generate the same events in the composition.

7 CONCLUSION

This paper focused on an automated mapping of a business process specification to a diagnostic model. By using our diagnosis module the complexity of diagnosis can be hidden from system administrators by outsourcing this functionality to a third party agent. The proposed approach enhances the automated diagnosis for a large number of compositions. This section briefly discusses the work and possible future work.

Scalability. There are two aspects to this. At runtime there is a need to compare a set of symptoms with each column of the problem code (PC) matrix. There has been considerable work on making this fast as noted in (Steinder and Sethi, 2004) and the work on a network fault management system (Yemini et al., 1996) shows that the use of the codebook can be very effective at run-time. This suggests that this approach will be scalable at run-time for service compositions. The second aspect is the generation of the PC matrix. This requires two algorithms: mdfs and pathGenerator. The mdfs algorithm is based on a modified depth-first search algorithm. Although compositions may be large, it is unlikely they will be so large that it would not be feasible to run the algorithms. We note that the generation of the PC matrix only needs to be done once for a specific composition. If a web service is replaced by another web service there is no need to generate a new PC matrix. If the composition changes then a new PC matrix needs to be generated. However, as future work will look at reusing part of the computation of the PC matrix for an older version of the application in order to reduce the time to create a new PC Matrix if the application topology changes.

Granularity. The granularity of the diagnosis model is limited to each service. If a service is considered to be a problem then a set of tests needs to be carried out to investigate why the service is a problem e.g., is the host down; is the service down. Furthermore it may be possible to use information in error messages to improve the granularity. This will be a topic of investigation for further studies. However, we note that for recovery purposes the level of granularity may often be satisfactory. If a service often violates its SLA then it may feasible to replace it with another service of the same type. The reasons for SLA violation are not necessarily relevant.

Mappings. This work considered only mapping from a BPMN model to a codebook fault diagnosis model. Further work will look at other businesses processes specifications as well as other fault diagnostic approaches. The current version of the diagnosis module only uses the the codebook technique. Since the coding phase is performed only once, the codebook approach is very fast, robust, and efficient. However, the accuracy of the codebook technique is hard to predict when more than one problem occurs with overlapping sets of symptoms. In addition, since each change of system configurations requires regenerating the codebook, the technique is not suitable for environments with dynamically changing dependencies (Steinder and Sethi, 2004). We will enable the module to use several event correlations techniques by which the module will be able to regenerate more efficient diagnostic knowledge bases.

ACKNOWLEDGEMENTS

The research for this paper was financially supported by the Ministry of Education of Saudi Arabia, and College of Computer Science and Engineering at Taibah University[2] and the Natural Sciences and Engineering Research Council of Canada (NSERC).

REFERENCES

Alam, S. (2009), Fault management of web services, Master, University of Saskatchewan.

Alonso, G., Casati, F., Kuno, H. and Machiraju, V. (2004), *Web Services: Concepts, Architectures and Applications*, 1st edition edn, Springer.

Angeli, C. and Chatzinikolaou, A. (2004), 'Online fault detection techniques for technical systems: A survey', *International Journal of Computer Science and Applications* 1, 51–64.

Ardissono, L., Console, L., Goy, A., Petrone, G., Picardi, C. and Segnan, M. (n.d.), 'Towards self-diagnosing web services', http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.75.1874.

Bahati, R. M., Bauer, M. A. and Vieira, E. M. (2007), Policy-driven autonomic management of multi-component systems, *in* 'Proceedings of 2007 the conference of the center for advanced studies on Collaborative research', ACM, pp. 137–151.

Caldwell, C. (1995), 'Graph Theory Glossary', http://www.utm.edu/departments/math/graph/glossary.html#b. Online; accessed 05-June-2011.

Eclipse (2011), 'BPMN Modeler', http://eclipse.org/bpmn/. Online; accessed 17-Oct-2011.

Endert, H., Hirsch, B., Küster, T. and Albayrak, S. (2007), Towards a mapping from bpmn to agents, Proceedings of the 2007 international workshop and 2007 conference on Service-oriented computing: agents, semantics, and engineering, Springer-Verlag, Berlin, Heidelberg, pp. 92–106.

Garza, A., Serrano, J., Carot, R. and Valdez, J. (2007), Modeling and simulation by petri networks of a fault tolerant agent node, *in* 'Analysis and Design of Intelligent Systems using Soft Computing Techniques', Vol. 41 of *Advances in Soft Computing*, Springer Berlin / Heidelberg, pp. 707–716.

Hanemann, A. (2007), Automated IT Service Fault Diagnosis Based on Event Correlation Techniques, PhD thesis, LMU Mnchen: Faculty of Mathematics, Computer Science and Statistics.

Hasan, M. S. (2011), Policy Based Third Party Web Service Management, Master, University of Western Ontario.

Hwang, I., Kim, S., Kim, Y. and Seah (2010), 'A survey of fault detection, isolation, and reconfiguration methods', *Control Systems Technology, IEEE Transactions on* 18(3), 636–653.

Kätker, S. and Paterok, M. (1997), Fault isolation and event correlation for integrated fault management, *in* 'Integrated Network Management V', Springer, pp. 583–596.

Kliger, S., Yemini, S., Yemini, Y., Ohsie, D. and Stolfo, S. (1995), A coding approach to event correlation, *in* 'Integrated Network Management IV', Springer, pp. 266–277.

Lins, F., Damasceno, J., Souza, A., Silva, B., Aragão, D., Medeiros, R., Sousa, E. and Rosa, N. (2012), 'Towards automation of soa-based business processes', *International Journal of Computer Science, Engineering and Applications* 2(2), 1–17.

MacKay, D. J. (2005), Binary codes, *in* 'Information Theory, Inference & Learning Algorithms', Cambridge University Press, pp. 206–227.

Morán, D., Vaquero, L. M. and Galán, F. (2011), Elastically ruling the cloud: specifying application's behavior in federated clouds, *in* 'Cloud Computing (CLOUD), 2011 IEEE International Conference on', IEEE, pp. 89–96.

Papazoglou, M. P. and Van Den Heuvel, W.-J. (2007), 'Service oriented architectures: approaches, technologies and research issues', *The VLDB journal* 16(3), 389–415.

Peng, Y. and Reggia, J. A. (1990), *Abductive inference models for diagnostic problem-solving*, Springer-Verlag New York, Inc.

Steinder, M. and Sethi, A. S. (2004), 'A survey of fault localization techniques in computer networks', *Science of Computer Programming* 53(2), 165–194.

Tiffany, M. (2002), 'A Survey of Event Correlation Techniques and Related Topics', http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.19.5339. Online; accessed 19-Dec-2010.

Tighe, M. and Bauer, M. (2010), Mapping policies to a causal network for diagnosis, *in* '6th International Conference on Autonomic and Autonomous Systems', pp. 13–19.

Yemini, S. A., Kliger, S., Mozes, E., Yemini, Y. and Ohsie, D. (1996), 'High speed and robust event correlation', *Communications Magazine, IEEE* 34(5), 82–90.

Zhang, J., Huang, Z. and Lin, K.-J. (2012*a*), A hybrid diagnosis approach for qos management in service-oriented architecture, *in* 'Web Services (ICWS), 2012 IEEE 19th International Conference on', IEEE, pp. 82–89.

Zhang, J., Huang, Z. and Lin, K.-J. (2012*b*), A hybrid diagnosis approach for qos management in service-oriented architecture, *in* '19th IEEE International Conference on Web Services', pp. 82–89.

[2]Taibah University site https://www.taibahu.edu.sa/Pages/AR/Home.aspx