Workflow Refactoring for Maximizing Concurrency and Block-Structuredness

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Abstract—In the era of Internet and big data, contemporary workflows become increasingly large in scale and complex in structure, introducing greater challenges for workflow modeling. Workflows are not with maximized concurrency and block-structuredness in terms of control flow, though languages supporting block-structuredness (e.g., BPEL) are employed. Existing workflow refactoring approaches mostly focus on maximizing concurrency according to dependences between activities, but do not consider the block-structuredness of the refactored workflow. It is easier to comprehend and analyze a workflow that is block-structured and to transform it into BPEL-like processes. In this paper, we aim at maximizing both concurrency and block-structuredness. Nevertheless, not all workflows can be refactored with a block-structured representation, and it is intractable to make sure that the refactored workflows are as block-structured as possible. We first define a well-formed dependence pattern of activities. The control flow among the activities in this pattern can be represented in block-structured forms with maximized concurrency. Then, we propose a greedy heuristics-based graph reduction approach to recursively find such patterns. In this way, the resulting workflow is with maximized concurrency and its block-structuredness approximates optimality. We show the effectiveness and efficiency of our approach with real-world scientific workflows.

Index Terms—Workflow refactoring, activity dependence, concurrency maximization, block-structuredness, synchronization links

1 INTRODUCTION

Workflows or processes are a series of inter-related activities targeted at achieving specific business functions. With the rapid advancement of cloud technology and the availability of ever more services, workflows are becoming one of the mainstream ways to construct software systems [1], [2], [3]. Meanwhile, service-based workflows grow increasingly large and their structure is becoming increasingly complex [1]. Modelling and changing workflows are a challenge [1], [3], [4]. Generally, workflows are expected to be free of both control flow errors (e.g., deadlocks) and data flow errors (e.g., activity input is undefined) [5], [6], [7], [8]. Maximizing concurrency in the control flow, with respect to the data flow, is also critical, and has recently received more attention in the literature [9], [10], [11], [12]. Concurrency maximization refers to the property that activities without dependences (including control dependences, data dependences [13]) should be executed in parallel. In this paper, we study BPEL-like workflows (workflows for short) [14]. However, even for the XML style, as pointed out in a recent empirical study [1], not all developers are familiar with good design practices for BPEL-like workflows. Thus, it is questionable whether real-world workflows are modeled with maximized concurrency.

While most control flow and data flow errors lead to failures of the workflow [5], [7], [15], a workflow does not necessarily fail if it is not designed with maximized concurrency. However, such non-maximized concurrency does affect the quality of workflows [16]; for example, the makespan of a workflow could increase in such situations. In the worst case scenario, non-maximized concurrency between communicating activities could reduce the success probability of a workflow (service) collaboration [10]. Take the workflows $P_1$ and $P_2$ in Fig. 1, for example: $P_1$ and $P_2$ share compatible interfaces (communicating activities) while $P_1$ ($P_2$) invokes (notation ‘!’) the operation $A$ ($B$) provided by $P_2$ ($P_1$) before receiving (notation ‘?’) the invocation of its provided operation $A$ ($B$) from $P_2$ ($P_1$). Assume that activities $A$ and $B$ in $P_1$ are independent, that is, $P_1$ is not designed with maximized concurrency because of the unnecessary sequence order between $A$ and $B$. This prevents $P_1$ from being composed with $P_2$ (and other similar workflows) to avoid a potential deadlock. However, if $A$ and $B$ are executed in parallel, then, $P_1$ and $P_2$ can be composed, thus, improving the success probability of the workflow collaboration. For the reasons identified above, non-maximized concurrency should be avoided.

Recently, a number of approaches to workflow refactoring have been proposed [17], [9], [10], [11], [16], [12]. For example, Wang et al. first transform BPEL workflows into automata then employ Petri nets synthesis [18] to obtain a workflow with maximized concurrency [11]. Jin et al. propose to leverage workflow mining (i.e., the $\alpha$-algorithm [19]) for workflow refactoring such that activities without data dependences can be executed in parallel [12]. Though some of these approaches achieve maximized concurrency, it is...
Fig. 1. An illustrating example showing maximized concurrency can improve the success probability of workflow collaboration.

not considered whether the refactored workflow is block-structured. Block-structuredness is a central workflow design principle [4], which means that for every node with multiple outgoing edges (i.e., a split), there exists a corresponding node with multiple incoming edges (i.e., a join) such that the workflow fragment between the split and the join forms a block [20]. If a workflow model block-structured, data flow analysis (e.g., data races) is made easier. Otherwise, users (e.g., workflow modelers) may have difficulty in understanding, analyzing, and testing its business logic. Furthermore, it is difficult for programmers to transform unstructured workflow models into popular block-structured workflow languages such as BPEL [14], [21]. For an approach which obtains the block-structured control flow (i.e., the approach in [11]), maximized concurrency is not ensured. One may argue that we can maximize concurrency and then block-structuring or reversely by combining these two existing approaches. Unfortunately, this solution is infeasible because the approach in [11] sacrifices concurrency for block-structuredness. In this paper, the control flow of a workflow is regarded as optimal if it ensures maximized concurrency and block-structuredness. To our best knowledge, our work is the first to consider both concurrency and block-structuredness maximization.

To address this bi-objective problem, we propose a novel workflow refactoring approach. For this, we first analyze activity dependences (e.g., control dependences, data dependences [13]) in the original workflow and capture them into a workflow dependence graph (WDG) from which we seek the optimal control flow of activities. We define a well-formed dependence pattern of activities whose control flow is block-structured with maximized concurrency. Specifically, the control flow can be specified using only sequential and parallel structures (Other structures are also considered but they are irrelevant to concurrency maximization). The WDG of a workflow is not always well-formed, which is caused by a minimum set of extra dependence edges. Should these edges be removed, the resultant graph becomes well-formed. By leveraging BPEL links to synchronize different branches (threads) of a parallel structure, the removed edges are transformed into links in the final optimized workflow. Those workflow with minimum links in the parallel structures are regarded as maximized block-structuredness [21]. Unfortunately, it is intractable to determine the minimum number of edges to transform. Thus, we present a greedy heuristic algorithm which harnesses the predecessors and successors of nodes (activities) to search well-formed patterns in the WDG. Although, our algorithm cannot always guarantee that the number of introduced links is minimal, we find that it is efficient in approximating an optimal control flow with minimal links.

We realize our approach and evaluate it based on a set of real-world scientific workflows, because they are sufficiently complex dependence graphs to evaluate the effectiveness and efficiency of our approach. The experimental results show that: (1) Our approach obtains BPEL-like workflows with maximized concurrency, i.e., activities without dependences are executed in parallel. (2) The obtained BPEL-like workflows contain few links. For the real-world DAGs (scientific workflows) employed in our experiment, the number of introduced links ranges from 0 to 8 and is 2.37, on average. (3) Our approach is efficient. The approach only takes 5.0 to 47.4 milliseconds (ms) to refactor scientific workflows with the number of nodes ranging from 7 to 85.

To sum up, this paper extends and improves our previous work [10] and makes the following new contributions:

1) We propose that unoptimized sequences (cf. Definition 7) can be regarded as another type of anti-pattern for workflow modelling and design, which are related to the interplay of both control flow and data flow; thus, complementing existing anti-patterns focusing either on control flow or data flow.

2) We define the notion of well-formed patterns in WDGs. The optimal control flow relations of activities in well-formed patterns are block-structured with maximized concurrency, which can be specified only with sequential and parallel structures.

3) Based on well-formed patterns and the semantics of links, we present a graph reduction approach, with the proof of its soundness, which guarantees obtaining the workflows with maximized concurrency and few links from irregular WDGs.

4) We implement our approach and experimentally evaluate it with a representative set of real-world scientific workflows; results demonstrate the effectiveness and efficiency of our approach.

The remainder of this article is organized as follows. Section 2 introduces some background information necessary for understanding this work. Section 3 formulates the research problem and provides an overview of our approach. Section 4 elaborates on our solution. Section 5 reports our experimental results. Section 6 reviews related work while Section 7 concludes the paper.

2 Preliminaries

Our refactoring approach is designed for BPEL [14] and workflow languages which also use links (or similar rules) to synchronize different branches in parallel structures. We use graph models (cf. Definition 1) instead of XML (BPEL) to represent workflows to improve readability. Since our refactoring only focuses on transforming unnecessary sequential structures into parallel structures, there is no need for the model to capture all syntax and semantics of BPEL. More specifically, commonly-used structured activities of BPEL [14], such as sequence (sequential structures), flow...
(parallel structures), if, switch, pick (alternative structures), while, repeatUntil (iterative structures) and their nested forms can all be expressed by our workflow model (cf. Definition 1). Links, inspired by BPEL syntax, are used to synchronize different branches of parallel structures. In BPEL, links can be associated with transition conditions, which is not considered in this paper.

**Definition 1 (Workflow Model).** A workflow is modeled as a four-tuple \( W = (N, E, I, O) \) such that:

- \( N \) is a set of nodes, where \( A_0, A_n \) represent the beginning and the ending of \( W \); \( N_b \) is the set of basic activities, and \( N_s \) is a set of structured activities.
- \( E \subseteq N \times N \) is a set of directed edges between nodes, representing the order between activities. An edge is called a link if it is between two nodes in different branches (threads) of a parallel structure, representing synchronization that reduces the parallelism.
- \( I, O : N \rightarrow 2^D \) are functions assigning input and output parameters to activities (basic activities and decision activities) in \( N \), where \( D \) is the set of data variables defined or used in \( W \).

In our notation for workflows, rounded rectangles, diamonds, and bars represent basic activities, decisions (the start of alternative and iterative structures), and the start (And-split) or the end (And-join) of parallel structures, respectively.

Different activities in a workflow can be inter-related by dependences. There are two common kinds of activity dependences in a workflow: control dependence and data dependence. Control dependence and data dependence are well-established notions in the field of programming language and software engineering [15], which is also the foundations of our refactoring approach. In the following, we formally introduce them (cf. Definitions 4 and 5) based on our workflow model. To define control dependence, we first introduce the concepts of path and post-dominance.

**Definition 2 (Path).** A path \( \rho \) from \( A \) to \( B \) in a workflow \( W = (N, E, I, O) \) is a sequence of one or more edges \((V_1, V_2), (V_2, V_3), \ldots, (V_{n-1}, V_n)\) in \( W \), where \( V_i \in N \), \( 1 \leq i \leq n \), \( V_1 = A \), and \( V_n = B \).

**Definition 3 (Post-dominance).** In a workflow model \( W \), an activity (node) \( A_j \) is post-dominated by another activity \( A_i \) if each directed path from \( A_i \) to the ending node \( A_e \) (not including \( A_i \)) contains \( A_j \).

**Definition 4 (Control Dependence).** In a workflow model \( W \), an activity \( A_j \) is control-dependent on another activity \( A_i \) iff there exists a directed path \( \rho \) from \( A_i \) to \( A_j \) such that any activity \( A_k \) in \( \rho \) (excluding \( A_i \) and \( A_j \)) is post-dominated by \( A_j \) and \( A_i \) is not post-dominated by \( A_j \).

Data dependences are three kinds: true dependence, anti-dependence and output dependence [13], [22].

**Definition 5 (Data (True) Dependence).** In a path \( \rho \) of workflow model \( W \), an activity \( A_j \) is true-dependent on another activity \( A_i \) iff there is a variable \( v \in I(A_j) \cap O(A_i) \) and in \( \rho \), there is no \( A_k \) between \( A_i \) and \( A_j \) such that \( v \in O(A_k) \).

Anti-dependence and output dependence are defined similarly by replacing \( v \in I(A_j) \cap O(A_i) \) with \( v \in O(A_j) \cap I(A_i) \), and \( v \in O(A_j) \cap O(A_i) \), respectively. Besides control dependence and data dependence, in BPEL, there is an async-invocation dependence between a one-way invoke activity and the receive activity responsible for receiving the result of the invoke [10]. All activity dependences (including implicit dependences in specific applications) in a workflow can be captured in its dependence graph.

**Definition 6 (Workflow Dependence Graph (WDG)) [22], [10].** A workflow dependence graph of a workflow \( W = (N, E, I, O) \) is a directed graph \( WDG = (N', E') \) such that:

- \( N' \subseteq N \) is a set of nodes representing activities of the workflow.
- \( E' \subseteq N' \times N' \) is a set of directed edges, and an edge \((A_i, A_j) \in E' \) directed from \( A_i \) to \( A_j \) denotes an activity dependence (e.g., control dependence, data dependence) between the two activities denoted by \( A_i \) and \( A_j \).

For a control dependence edge \((A_i, A_j)\), if \( A_i \) is a decision activity representing an alternative structure (e.g., if, switch), \((A_i, A_j)\) is labelled either as “T” or as “F” depending on whether \( A_j \) occurs when the decision is true. If \( A_i \) is a decision activity representing an iterative structure (e.g., while, repeatUntil), \((A_i, A_j)\) is labelled as “T”. If an activity \( A_j \) is not control-dependent on any activity, we assume that it is control-dependent on the starting activity \( A_b \) (also called “entry”) of the workflow. In this way, \( A_e \) is always control-dependent on \( A_b \) but we usually omit \( A_e \) in the WDG, because it has nothing to do with refactoring.

Fig. 2 illustrates the workflow model of a shipping service whose business logic can be expressed by BPEL: \( <\text{sequence } A_1, A_2, A_3\text{-while}<\text{sequence } A_4, A_5, A_6/>/> \). This workflow sends items in groups until the customer’s order is fulfilled. From Fig. 2a, we can see that activities \( A_4 \) and \( A_5 \) are post-dominated by \( A_6 \), while \( A_3 \) is not. Thus, according to Definition 4, \( A_6 \) is control-dependent on \( A_3 \). Similarly, \( A_4 \) and \( A_5 \) are also control-dependent on \( A_3 \). Since activities \( A_1, A_2, A_3 \) are not control-dependent on any activity, they are regarded as to be control-dependent on the beginning activity “Entry”. The WDG of the workflow is shown in Fig. 2b where the solid lines labeled “T” denote control dependences, other solid lines data dependences, and the dashed lines loop-carried data dependences [13]. If we discard loop-carried data dependences and those caused by data races, the WDG turns into a DAG. As is discussed in our previous work [23], the discard facilitates the determination of control-flow relations of nodes in the WDG.

**3 Problem and Approach Framework**

In this section, we first formulate the research problem, and then present an overview of our approach.

**3.1 Problem Formulation**

To formulate the problem, we first define a novel workflow anti-pattern (cf. Definition 7). Similar to BPEL, we use \( s = <\text{sequence } A_1, A_2, \ldots, A_n/> \) to represent a sequence of activities \( A_1 \ldots A_n \).
Definition 7 (Unoptimized Sequence). Given a sequence $s = <A_1, A_2, ..., A_n>$ in a workflow $W$, for all $i (1 \leq i < n)$, if $<A_i, A_{i+1}>$ is an activity dependence, then $s$ is a necessary sequence. Otherwise, $s$ is an unoptimized sequence, i.e., it is unnecessary that all activities execute in a sequential order.

The input workflow can have flow, but only unoptimized sequence (it can be nested in a flow) are considered. For example, the workflow depicted in Fig. 2a contains an unoptimized sequence $s = <A_4, A_5, A_6>$ (this sequence is nested in an iterative structure while), as there is no dependence between activities $A_5$ and $A_6$ (cf. Fig. 2b). Informally, our goal is to automatically identify these unoptimized sequences and re-arrange those activities to make sure that activities without dependencies are executed in parallel while the number of links introduced in parallel structures is minimum. More formally, the workflow refactoring problem is described as follows:

The refactoring problem is to optimize the control flow of a workflow $W$ to obtain a new workflow $W'$ which shares the same WDG with $W$ such that:

- $W'$ involves no unoptimized sequences.
- $W'$ is as block-structured as possible, i.e., with a minimum number of links in parallel structures (flows).

3.2 Approach in a Nutshell

Fig. 3 illustrates the three stages of our approach:

1) WDG construction. Activity dependences (including control and data dependences) of the workflow are analyzed and captured in the WDG.

2) Unoptimized sequence identification & parallelization. Unoptimized sequences are identified via the WDG. Activities with no direct or transitive dependences are arranged in parallel structures.

3) User confirmation. Since there may be implicit dependences (the activities need executing in sequence), each parallelization opportunity identified in Stage 2 is provided to users (e.g., workflow modellers and programmers) for final confirmation. An optimization opportunity is abandoned if it is not passed user confirmation.

Although our attention is focused on transforming sequences into flows (could be with links), our approach applies to all workflows that are defined in Definition 1. Since WDG can be obtained with existing approaches [13],[22] and the last stage is straightforward, we focus on the second stage in Section 4.

4 Refactoring Approach

To better understand our approach, we first examine the structure of the WDG. If only edges of control dependences are kept, the WDG degenerates into a tree with a single-control WDG ("Entry") as its root [13],[22]. In the tree, the root, each inner node represents a decision activity, while each leaf node represents a basic activity. For instance, in Fig. 2b, the inner node $A_3$ denotes a decision activity while, while other nodes (except “Entry”) denote basic activities.

Because of nested control flow, the refactoring is performed from the inner sequence to the outer one. For the workflow in Fig. 2a, the inner $<A_1, A_2, A_3/>$ is refactored first before the outer $<A_4, A_5, A_6/>$. Next, we first present our approach to local refactoring, i.e., seeking the optimal control flow relations for the activities of the innermost block (sequence). Then, we show how to identify optimization opportunities across different blocks, referred to as global refactoring.

4.1 Local Refactoring

For local refactoring, we first consider a single-control WDG in which there is only one control node (decision activity or $A_3$). Other nodes in the single-control WDG can be partitioned into one, two or more classes according to the labels (e.g., “T”, “F”) on the edges from the control node to these nodes. Nodes (activities) in different classes are mutually-exclusive, i.e., they cannot be executed together. The refactoring is applied to different classes of nodes independently. Although nodes in the same class can be
related by edges of data dependences, asyn-invocation dependences, and implicit dependences, there is no need to differentiate them for refactoring.

4.1.1 Optimal Control Flow Graph

In graph theory, a sub-graph $SG$ of $G = (N, E)$ is said to be induced by a node set $SN$ ($SN \subseteq N$) if $SG$ has all edges of $G$ with both endpoints in $SN$. Now, we discuss how to seek the optimal control flow relations for the nodes in the same class based on the sub-graph (DAG) they induce.

A weakly connected component [24] is a maximal sub-graph of a directed graph such that if replacing all of its directed edges with undirected edges produces a connected (undirected) graph, that is, any two nodes, say, $A_i$ and $A_j$, are reachable from each other. Only two cases exist: the sub-graph is a weakly connected component (WCC), or it involves more than one WCC. For the latter case, the control flow relation among these WCCs is specified as flow, as they are independent of one another. To determine the control flow relations of the nodes inside a WCC, we need to ensure that the determined control flow relations of the nodes are consistent with the dependences in the WCC such that concurrency degree can be maximized. This problem can be regarded as an extension to the problem of topological sorting [25], because all possible topological sorts correspond to the trace set of the obtained control flow graph (cf. Theorem 3). Here, our goal is to obtain the optimal control flow graph (cf. Definition 8) from the WCC.

Definition 8 (Optimal Control Flow Graph). Given a DAG $G = (N, E)$, the corresponding control flow graph $G_{CF}$ derived from $G$ is optimal if the following two conditions are satisfied:

- For any two nodes $A_p$ and $A_q$, if $A_p(A_q)$ is reachable from $A_q(A_p)$ in $G$, the control flow between them in $G_{CF}$ is sequence, and $A_p(A_q)$ precedes $A_q(A_p)$; otherwise, the control flow between them in $G_{CF}$ is flow.
- $G_{CF}$ is as block-structured as possible, i.e., minimum number of links is involved.

The first condition of Definition 8 ensures concurrency is maximized, viz., no unoptimized sequences are involved. The second condition ensures maximized block-structuredness. Although our refactoring approach aims at this bi-objective optimization, as we will show in Section 4.1.3, it is difficult to guarantee the second condition. Fortunately, if the first condition is satisfied, the corresponding workflow shares the equivalent behavior with the refactored workflow satisfying both conditions [26], because they are trace-equivalent [27].

4.1.2 Graph Reduction

It is challenging to obtain the optimal control flow graphs because of the complex structure of WCCs. Here, we present a graph reduction approach to address this problem, which includes the following three steps:

1. A trace of $G_{CF}$ is a linear extension of the happens-before relations in $G_{CF}$.
2. Obtain the transitive reduction of the WCC. The transitive reduction [28] preserves the reachability relations in the WCC, but has fewer dependence edges. This facilitates seeking the optimal control flow relations of nodes in the WCC. In the remainder of this paper, all mention of WCC refers to its transitive reductions.
3. Search well-formed patterns (cf. Definition 10) for reduction. In the WCC, control flow relations of well-formed patterns are block-structured and can be described with sequence and flow. After the control flow of a well-formed pattern is determined, we use a single node to replace the whole pattern in the WCC (cf. Reduction Rule 1) to facilitate identifying other well-formed patterns.

In the following, we explain Step 2 and Step 3. For convenience of describing the notion of well-formed pattern and the corresponding reduction rule, we first introduce the concepts of preset and postset.

Definition 9 (Preset, Postset). In a directed graph $G = (N, E)$, for any node $A_p \in N$, the preset of $A_p$ is defined as $\{A_p\} A_q \in N \land \langle A_q, A_p \rangle \in E$ and the postset of $A_p$ is defined as $A_p^* = \{A_q | A_q \in N \land \langle A_q, A_p \rangle \in E\}$. For a node set $SN$, the preset of $SN$ is defined as $SN^* = \{A_p | A_p \in SN \land A_q \in N \land \langle A_q, A_p \rangle \in E\}$ and the postset of $SN$ is defined as $SN^* = \{A_q | A_q \in SN \land A_p \in N \land \langle A_p, A_q \rangle \in E\}$.

Definition 10 (Well-formed Pattern). In a WCC $G = (N, E)$, a sub-graph $SG$ induced by a node set $SN = SN_1 \cup SN_2 \cdots \cup SN_n$ is regarded to be a well-formed pattern if for any $A_p, A_q \in SN_i (1 \leq i \leq n)$, the following two conditions are satisfied:

- $\langle A_p, A_q \rangle \notin E \land \langle A_q, A_p \rangle \notin E$.
- $A_p^* = A_q^* = SN_{i-1} \land A_p^* = A_q^* = SN_{i+1}$, where $SN_0, SN_{n+1} \subseteq N$, $SN_0 \cap SN = SN_{n+1} \cap SN = \emptyset$.

Note that in Definition 10, $SN_0$ and $SN_{n+1}$ are not subsets of $SN$, which indicates that the well-formed pattern is maximized already, which cannot be further enlarged.

Reduction Rule 1. In a WCC $G = (N, E)$, a well-formed pattern $SG$ induced by a node set $SN = SN_1 \cup SN_2 \cdots \cup SN_n$ can be reduced into a single node $S$ such that:

- $S^* = SN_1 \cap S^* = SN_n^*$.
- $S = <sequence \ <flow \ SN_1 \ /> \ , \ \cdot \cdot \cdot \ , \ <flow \ SN_n \ /> \ >$, denoting that nodes in $SN_i (1 \leq i \leq n)$ are in a parallel structure, and $SN_1, ..., SN_n$ are in a sequential structure.

2. The transitive reduction of a directed graph $D$ is another directed graph $D'$ with the same vertices and as few edges as possible, such that if there is a (directed) path from vertex $s$ to vertex $t$ in $D$, then there is also such a path in the reduction $D'$.
The source activity and the target activity of an introduced link are in a parallel structure (i.e., a flow).

**Proof.** We prove Theorem 1 by contradiction. According to our approach, a link in the resultant workflow corresponds to a removed edge in the WCC (dependence graph). Let \(<A_p, A_q>\) be such a removed edge. Assume that activities \(A_p\) and \(A_q\) are not in a flow, and thus, they must be in a sequence. According to Reduction Rule 1, there must exist a (transitive dependence) path from \(A_p\) to \(A_q\) in the WCC, say \(\rho = <A_p, A_1> \ldots <A_q, A_q>\). However, the co-existence of \(\rho\) and \(<A_p, A_q>\) contradicts the fact that WCC is a transitive reduction. Thus, Theorem 1 holds.

**Theorem 2.** Our graph reduction approach can obtain a control flow graph with maximized concurrency from a DAG.

**Proof.** Let \(A_p\) and \(A_q\) be any two nodes in a DAG. If \(A_q\) is reachable from \(A_p\) in the DAG, or reversely, in the obtained control flow graph, they are either in a sequence according to Reduction Rule 1, or linked in a flow according to the semantics of links. In both situations, \(A_p\) and \(A_q\) are executed in parallel. Thus, the first condition of Definition 8 is met, and thus Theorem 2 holds.

The overall behavior of a workflow can be expressed by its set of complete traces (from the beginning to the end of the workflow). If at least one parallelization opportunity is confirmed by users, the trace set of the refactored workflow subsumes that of the original workflow. Theorem 3 demonstrates the relation between the trace set of the control flow graph with maximized concurrency and the set of topological sorts of the DAG (dependence graph).

**Theorem 3.** A control flow graph derived from a DAG satisfies maximized concurrency if and only if its complete trace set equals the set of all possible topological sorts of the DAG.

**Proof.** Assume that \(G_{CF}\) is a control flow graph derived from the DAG. Let \(S_1\) be the set of all possible topological sorts of the DAG and \(S_2\) the set of all complete traces of \(G_{CF}\). We proceed by proving sufficiency and necessity.

**Sufficiency.** If \(S_1 = S_2\), we show \(G_{CF}\) meets maximized concurrency (cf. Definition 8). For any two nodes \(A_p\) and \(A_q\) in the DAG,

1) If \(A_q\) (\(A_p\)) is reachable from \(A_p\) (\(A_q\)) in the DAG, for any topological sort \(s\) in \(S_1\), \(A_p\) (\(A_q\)) precedes \(A_q\) (\(A_p\)) in \(G_{CF}\). Since \(S_2 = S_1\), the control flow relation between \(A_p\) and \(A_q\) in \(G_{CF}\) is sequence.

2) Otherwise, there must exist at least two topological sorts \(s_1\) and \(s_2\) in \(S_1\) such that \(A_p\) precedes \(A_q\) in \(s_1\) and \(A_q\) precedes \(A_p\) in \(s_2\). Since \(S_2 = S_1\), the control flow relation between \(A_p\) and \(A_q\) in \(G_{CF}\) is flow.

**Necessity.** We prove \(S_1 \subseteq S_2\) and \(S_2 \subseteq S_1\).

1) Let \(s\) be any topological sort in \(S_1\) and \(A_i\) and \(A_{i+1}\) are any two adjacent activities in \(s\). This implies either \(<A_i, A_{i+1}>\) is an edge of the DAG, or \(A_i\) and \(A_{i+1}\) are not reachable from each other. Since \(G_{CF}\) meets maximized concurrency, in either case, there must be a complete trace \(\sigma\) of \(G_{CF}\) such that \(A_i\) and \(A_{i+1}\) are adjacent (\(A_i\) directly precedes \(A_{i+1}\)) in \(\sigma\). Owing to the arbitrariness of \(A_i\) and \(A_{i+1}\), the order...
between activities in σ is preserved in σ′, i.e., σ = σ′. Hence, σ is a complete trace of \( G_{\text{CF}} \), i.e., \( S_1 \subseteq S_2 \).

2) Let σ be an arbitrary complete trace in \( S_2 \), and \( A_i \) and \( A_{i+1} \) are any two adjacent activities in σ. In \( G_{\text{CF}} \), the control flow relation between \( A_i \) and \( A_{i+1} \) is either sequence (\( A_i \) directly precedes \( A_{i+1} \)) or flow. Since \( G_{\text{CF}} \) meets maximized concurrency, for the former case, \(<A_i, A_{i+1}>\) must be an edge in the DAG; for the latter case, neither \( A_i \) nor \( A_{i+1} \) can be reached from the other. In either case, there must exist a topological sort σ′ of the DAG such that \( A_i \) and \( A_{i+1} \) are adjacent (\( A_i \) directly precedes \( A_{i+1} \)) in σ′. Owing to the arbitrariness of \( A_i \) and \( A_{i+1} \), the order between activities in σ is preserved in σ′, i.e., \( \sigma = \sigma' \). Hence, σ is a topological sort of the DAG, i.e., \( S_2 \subseteq S_1 \).

To sum up, Theorem 3 is proven.

If there are optimization opportunities (i.e., unoptimized sequences) in the original workflow, the restructured workflow derived from the DAG will involve more traces than the original workflow; that is, the trace set of the original workflow is a subset of that of the restructured workflow. This is of great significance for service (workflow) collaboration, because more behaviour (traces) implies more compatible partners in workflow composition [10].

### 4.1.3 Strategy for Introducing Links

Reduction Rule 1 and the semantics of links are complementary. On the one hand, if we incorporate all activities of a WCC into a flow structure and introduce a link for each edge in the WCC, maximized concurrency is achieved. Nonetheless, the obtained control flow graph is far from block-structured. On the other hand, Reduction Rule 1 can obtain the optimal control flow graph without using links provided that the WCC is well-formed. Due to the irregularity of WCC, we have to combine these two solutions together, and the goal is to introduce a minimum number of links. The well-formed pattern (cf. Definition 10) is called a series-parallel directed graph (or minimal vertex series-parallel directed graphs in particular) in graph theory [29]. Thus, our goal equals to obtain the maximum series-parallel subgraph from a DAG. It is known that this problem is NP-hard for undirected graphs [30], [31], but whether the result is generalized to directed graphs is still an open problem [29].

One may come up with the following straightforward algorithm to introduce a minimum number of links for graph reduction. Given an arbitrary DAG \( G = (N, E) \), its transitive reduction \( G^* = (N, E^*) \) can be obtained. First, the algorithm checks whether \( G^* \) is a well-formed pattern. If yes, it terminates. Otherwise, it precedes by removing any one edge from \( G^* \), and determines whether the resultant \( G^* \) is well-formed. In the second step, there could be \( C_1^n \) attempts, where \( n = |E^*| \). For each of the \( C_1^n \) attempts, the algorithm terminates when \( G^* \) becomes well-formed. Otherwise, it goes on by removing any two edges from \( G^* \), and determines whether \( G^* \) is well-formed. In the third step, there could be \( C_2^n \) attempts. The algorithm iterates in this way until \( G^* \) becomes well-formed. When it terminates, the number of edges removed must be minimum, and thus a minimum number of links for graph reduction is guaranteed. However, the number of attempts in the worst case is \( C_0^n + C_1^n + \ldots + C_n^n = 2^n \), which is intractable in practice.

### Algorithm 1 Local refactoring

| Input: The DAG-based dependence graph (WCC) \( G = (N, E) \) |
| Output: The obtained control flow graph w.r.t. the WCC |

1: Obtain the preset \(*A \) and postset \(*A \) for each node \( A \) in the WCC;
2: Find nodes whose presets and postsets are all the same. These nodes can be combined and reduced to a single node (i.e., \(<A_i, A_{i+1}>\)). Find a sequence of nodes \( A_1A_2\ldots A_n \) such that \( A_i^* = \{A_i\} \), \( A_i = \{A_i\} \), where \( 1 \leq i \leq n \). These nodes can be combined together and reduced to a single node (i.e., \(<A_i, A_{i+1}>\));
3: Find nodes whose presets (postsets) intersect. For each set (denoted as \( P \) of these nodes, obtain the difference set (denoted as \( D \)) of the presets (postsets) of these nodes. If edges with one endpoint in \( P \) and the other in \( D \) are removed, a well-formed pattern can be found, which is regarded as a candidate for reduction;
4: Use a greedy heuristic for the graph reduction. That is, utilize Reduction Rule 1 to reduce the well-formed pattern (including the nodes in \( P \) whose profit \( n/m \) is the largest, where \( m \) is the number of edges removed and \( n \) is the number of nodes that can be composed for reduction;
5: The locally optimal steps, i.e., steps 3 and 4, are iterated until the WCC is reduced into a single node.

With the above works, we propose a greedy-heuristic algorithm (Algorithm 1) to seek the optimal control flow graph. Algorithm 1 leverages the presets and postsets of nodes to find well-formed patterns. Note that we can optimize Step 3 in Algorithm 1 as follows. First, we identify activities whose presets or postsets are the same. Based on these sets of nodes, we can also obtain corresponding candidate subgraphs for the local optimization. If no activities meet this condition, then we use the operations in Step 3 to go on. The original operations in Step 3 are referred to strategy 1, and the optimization is referred to strategy 2. No matter which strategy is used in Step 3, our greedy heuristic does not guarantee to find the optimal solution (i.e., the minimal number of links), but rather yields solutions approximating the optimum in reasonable time. Strategy 2 does not guarantee introducing fewer links than Strategy 1 does, but it could be more efficient because it may generate fewer candidate subgraphs for the local decision. This will be validated in Section 5. The control flow relations obtained are always with maximized concurrency even if more than the minimum number of links are introduced.

Let us illustrate Algorithm 1 with an example. Fig. 6a shows a WCC representing a dependence graph. Our goal is to seek the optimal control flow relations of nodes (activities) in this WCC. Since the WCC is not well-formed, we need to remove some edges to obtain well-formed subgraphs whose control flow relations can be determined. According to Step 3 of Algorithm 1, we should find nodes whose presets or postsets intersect. For example, we can find a node set \( \{A_5, A_6\} \), where nodes \( A_5 \) and \( A_6 \) share the same postset, i.e., \( A^*_5 = A^*_6 = \{A_4\} \). Similarly, we can find all other candidate node sets: \( \{A_1, A_2\} \), \( \{A_3, A_4\} \), \( \{A_6, A_7\} \).
flows, global refactoring needs to identify optimization opportunities from the innermost sequence to the outermost one, as specified by Algorithm 2.

Algorithm 2 Global refactoring

Input: The WDG of the original workflow
Output: The restructured workflow

1: All control nodes (decision nodes and \( A_0 \)) of the resultant WDG are identified and pushed into a stack in the level traversal order beginning from the root (\( A_0 \)) of the subgraph (only control dependence is considered) of the WDG;
2: A control node \( A_n \) is popped from the stack. From \( A_n \), corresponding sub-workflow whose WDG is single-controlled is obtained. Thus, the sub-workflow can be refactored by Algorithm 1;
3: The corresponding single-control WDG is degenerated into its control node \( A_0 \) (cf. Reduction Rule 2)
4: Steps 3 and 4 are iterated until the control node stack becomes empty.

Reduction Rule 2. In a WDG \( G = (N, E) \), \( G_s = (N_s, E_s) \) is a single-control WDG induced by node set \( N_s \). \( G_s \) degenerates to its control node \( A_0 \) (also denoted as \( A_0' \)) while \( G \) reduces to \( G' = (N', E') \) such that: \( N' = N \setminus \{A_0\} \); \( E' = E \setminus \{(A_0, A_s) | A_s \in N \setminus N_s \wedge A_s \in N \setminus \{A_0\}\} \) \( \cup \{(A_0', A_s) | A_s \in N \setminus N_s \} \).

Fig. 7 illustrates Reduction Rule 2: The single-control WDG \( G_s \) degenerates to its control node \( A_0 (A_0') \), which facilitates the subsequent refactoring. Moreover, any edge with one endpoint in \( N \setminus \{A_0\} \) and the other endpoint in \( N \setminus N_s \) is “removed” (denoted by dashed directed edges). Such a “removed” edge will become into a link when its two endpoints are enclosed in a flow structure (cf. Theorem 1).

Our two reduction rules exhibit different functionalities. Reduction Rule 1 determines the block-structured control flow (sequence, flow) of activities in the dependence graph, whereas Reduction Rule 2 simplifies the WDG such that the problem of global refactoring is reduced to the one of local refactoring. We assume that the original BPEL-like workflows are block-structured and hence sound [32]. Since the links introduced cannot lead to errors, such as deadlocks, the soundness of the workflow is not compromised.

To refactor the process in Fig. 2a, we first traverse the sub-graph (tree in terms of control dependences) of the WDG in Fig. 2b following a level traversal order. After this step, the “Entry” node and the decision node \( A_3 \) are pushed into a stack. Secondly, \( A_3 \) is popped out from the stack, and Algorithm 1 is used to refactor \( \text{sequence } A_4, A_5, A_6/ \) into \( \text{sequence } A_4, \text{flow } A_3, A_6/ \).

4.2 Global Refactoring

We extend our approach to restructure workflows whose WDGs have more than one control node (a.k.a. multi-controlled WDGs). Due to the nested structure of work-
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In this section, we conduct an experimental evaluation to answer the following two research questions:

- **RQ1 - Effectiveness**: How effective is our approach in maximizing concurrency and block-structuredness for workflow refactoring? That is, on the one hand, does it neither miss real optimization opportunities, nor introduce false ones? On the other hand, does it introduce few links into the refactored workflows?
- **RQ2 - Efficiency**: How efficient is our refactoring approach (and other approaches) in maximizing concurrency and block-structuredness? Does our approach scale well in practice?

Our experiment was performed on a set of real-world scientific workflows by using a computer with 1.7 GHz CPU and 4 GB memory, running windows 8 and JDK 1.7.

### 5.1 Experimental Setup

**Approach Implementation**. In the experiment, we compare our approach with state-of-the-art refactoring approaches summarized in Table 1. We implement our approach in a prototype ProR, which can be found at: http://bit.ly/myProR. These three approaches do not require duplication of tasks. The approach BeehiveZ is based on a workflow mining technique, that is, the α-algorithm [19]. Note that the first three approaches are quite different in the following respects. First, the workflow models used in these approaches are heterogeneous. More specifically, CASS uses directed graphs, BeehiveZ employs Petri nets, and the workflow model adopted by our approach is similar to UML activity diagrams [33]. Second, decision activities are only explicitly modeled in some of the aforesaid models. Thirdly, these approaches utilize distinct analysis techniques to obtain the activity dependences. Despite these differences, the last and the vital step in all these three approaches is similar: they all leverage the workflow dependence graph (or activity dependences) to obtain the refactored workflows. Hence, we only focus on the last step of each approach to obtain a fair comparison.

**Data Set**. Since the performance of our approach significantly depends on the complexity of the dependence graph, we use real-world scientific (Taverna) workflows from myExperiment\(^3\) [34] for our evaluation. These scientific workflows tend to be more complex (not so strictly) with the increasing number of activities, which can discriminate different approaches. According to the number of activities (#Act) involved, we divide the workflows into three categories: simple (#Act < 30), medium (30 ≤ #Act < 50), and complex (50 ≤ #Act). We randomly select 10 subjects from each category and thus 30 scientific workflows are used. The 30 workflows are modeled with DAGs and each edge of the DAGs represents the dependence between two activities. Similar workflows are also used in [2], [35]. Based on the dependence relations in these DAGs, different refactoring approaches are utilized to seek the workflow models with the optimal control flow. This equals to transform the DAGs into BPEL-like workflows. The names (few are shortened for short), the number of activities (#Act), and the number of edges (#Edg) of the 30 workflows with references (“1”-“30”) are summarized in Table 2. To facilitate comparison, we introduce two notions. Given a scientific workflow \(W\), one, we utilize an ordered activity pair \(<A_p, A_q>\) to show that activity \(A_q\) is reachable from activity \(A_p\) in \(W\), and, two, we use an unordered activity pair \([A_p, A_q]\) to show that activities \(A_p\) and \(A_q\) are not reachable from each other in \(W\). \(<A_p, A_q>\) and \([A_p, A_q]\) are referred to as reachability pair and unreachability pair, respectively.

### Evaluation Criteria

Although workflow models (control flow graphs) obtained by different approaches are in different forms (directed graphs, Petri nets, UML activity diagrams), we can define general criteria to evaluate the obtained process models. Assume that \(W\) is the workflow model obtained from a DAG by using an approach from Table 1. We use an ordered pair \(<A_p, A_q>\) to show that activity \(A_p\) precedes activity \(A_q\) in \(W\), and an unordered activity pair \([A_p, A_q]\) to show that activities \(A_p\) and \(A_q\) are concurrently executed in \(W\). Let \(S\) and \(F\) be the sets of ordered pairs and unordered pairs in \(W\), and let \(R\) and \(U\) be the sets of reachability pairs and unreachability pairs in the DAG, respectively. The following criteria are used to evaluate different workflow refactoring approaches.

**Criterion 1: Checking Concurrency Maximization**. We adapt F-measure (i.e., \(F_1\)) of precision and recall [36] to measure to what extent a refactoring approach can achieve maximized concurrency, given by:

\[
\text{precision} = \frac{|S \cap R| + |F \cap U|}{|S \cup F|} \quad (1)
\]

\[
\text{recall} = \frac{|S \cap R| + |F \cap U|}{|R \cup U|} \quad (2)
\]

\[
F_1 = 2 \times \text{precision} \times \text{recall}/(\text{precision} + \text{recall}) \quad (3)
\]

The higher the value of the F-measure \((F_1)\), the better the corresponding workflow refactoring approach. \(F_1 = 1\) implies that the obtained workflow model is with maximized concurrency. \(F_1 < 1\) indicates that the approach fails to obtain maximized concurrency.

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**Table 1: Approaches Compared in the Experiments**

<table>
<thead>
<tr>
<th>Ref.</th>
<th>Refactoring approaches</th>
</tr>
</thead>
<tbody>
<tr>
<td>CASS</td>
<td>The approach proposed in [9]</td>
</tr>
<tr>
<td>BeehiveZ</td>
<td>The approach proposed in [12]</td>
</tr>
<tr>
<td>ProR</td>
<td>Our graph reduction-based approach</td>
</tr>
</tbody>
</table>
5.2 RQ1: Effectiveness

Before presenting the experimental results, we first use an example to show the advantage of our approach. Fig. 8a-c shows the workflow models (control flow graphs) transformed from the DAG (scientific workflow with reference “3” in our data set) in Fig. 8d by approaches CASS, BeehiveZ, and ProR, respectively. It follows that: the workflow model in Fig. 8a is block-structured, but the maximized concurrency is not satisfied, because some activities independent in Fig. 8a are executed in sequence; the workflow model in Fig. 8b (Petri net) satisfies maximized concurrency but is not block-structured, because some And-split (flowstar) or And-join (flowend) are missing; the workflow model in Fig. 8c satisfies maximized concurrency and is as block-structured as possible, that is, each flow begins with an And-split and ends with an And-join, while only one link from activity Split_string... to activity Filter_list... is introduced. Note that the And-splits and And-joins in Fig. 8c are used for illustration, and they correspond to <flow> and </flow>, respectively, in the final BPEL-like file. Our

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Fig. 8. Workflow models (control flow graphs) (a), (b), (c) transformed from (d) a real scientific workflow “Get TP53 By Exon” with CASS, BeehiveZ, and ProR, respectively.
TABLE 2
Experimental Results - RQ1: Effectiveness

<table>
<thead>
<tr>
<th>Ref.</th>
<th>Name</th>
<th>#Act</th>
<th>#Edg</th>
<th>CASS</th>
<th>BeehiveZ</th>
<th>ProR</th>
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<td></td>
<td></td>
<td></td>
<td></td>
<td>#split</td>
<td>#join</td>
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<td>1</td>
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<td>13</td>
<td>0.96</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>3</td>
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<td>4</td>
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<td>12</td>
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<td>1</td>
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</table>

The experimental results on all the 30 scientific workflows based on Criteria 1 and 2 are summarized in Table 2. The first column depicts the references 1-30 of the scientific workflows. The three sub-columns in the fifth and sixth columns report the F-measure ($F_1$), the number of AND-split (#split), and the number of AND-join (#join) of the workflow models obtained by the approach CASS and BeehiveZ, respectively. The first three sub-columns of the eighth column report $F_1$, #split, and #join of the workflow models obtained by our approach (ProR) and the fourth sub-column reports the corresponding number of links (#links) introduced in the obtained BPEL-like workflow models. Table 2 demonstrates:

CASS obtains block-structured workflow models from DAGs, because the AND-splits and the AND-joins are in pairs. However, $F_1$ of the workflow models obtained by CASS are below 1 (except scientific workflow “4”), which indicates that CASS fails to obtain the workflow models with maximized concurrency. In our experiment, we find that CASS does not introduce false optimization opportunities; i.e., it does not allow activities with direct and indirect dependences to be executed in parallel, but it may miss some real optimization opportunities, that is, activities without dependences are arranged to be executed in sequence. Surprisingly, for most well-formed DAGs (scientific workflows), i.e., “1”, “2”, “7”, “8”, “12”, and “20”, CASS fails to obtain workflow models with maximized concurrency. In summary, CASS sacrifices a number of optimization opportunities to make the workflow models block-structured.

$F_1$ of the workflow models obtained by BeehiveZ are all 1. This implies that BeehiveZ is able to derive from the DAGs the workflow models with maximized concurrency. However, for most cases, in the obtained workflow models, AND-splits and AND-joins are not in pairs. Hence, the obtained workflow models can hardly be expressed in BPEL. Therefore, we draw the conclusion that BeehiveZ cannot guarantee obtaining block-structured workflow models. In addition, since BeehiveZ is based on a well-known workflow mining technique (i.e., the $\alpha$-algorithm) for workflow refactoring, our experimental results also demonstrate that it is not the main goal of workflow mining to produce block-structured workflow models but to produce workflow models that justify the respective behaviour exhibited in the event logs.

$F_1$ of the workflow models obtained by our approach (ProR) remains 1, and the AND-splits and the AND-joins in these workflow models are in pairs. In addition, the number of links introduced by ProR is small. Notably, we do not know whether the number of introduced links is minimal, because there is no oracle for this. Nevertheless, for the well-formed scientific workflows with labels “1”, “2”, “4”, “7”, “8”, “12”, and “20”, the workflow models obtained by ProR involve no links; for the not well-formed scientific workflows with labels “3”, “5”, “6”, “11”, “14”, “17”, “23”, “26”, “27”, “28”, and “29”, the workflow models obtained by ProR involve no links.
only one link is introduced by ProR, respectively. Thus, for at least 14 of the 30 scientific workflows, ProR obtains workflow models with maximized concurrency and as block-structured as possible. For the other scientific workflows, ProR also introduces few links and the average number of links is 2.37 for these 30 workflows. Thus, ProR approaches to the optimal solution. Since scientific workflows tend to become more complex with increasing number of activities, the average number of links introduced increases from simple, medium, to complex workflows.

5.3 RQ2: Efficiency

Table 3 summarizes the runtime overhead of different refactoring approaches, where the first column shows the reference to the selection of the 30 scientific workflows we use. The two sub-columns of the last column report the runtime overhead for the two strategies of the third step in Algorithm 1, where the second strategy (Strategy 2) is the optimized one. According to Table 3:

All three approaches scale well. The runtime overhead of different approaches does not always increase with increasing workflow (DAG) size, because in addition to DAG size, the runtime cost also depends on the structural complexity (i.e., irregular dependence relations) of the DAG. However, the average runtime overhead increases from simple, medium, to complex workflows.

Our approach ProR is faster than BeehiveZ but slower than CASS. This is because ProR aims at maximizing both concurrency and block-structuredness, while other approaches only focus on one aspect. BeehiveZ is slowest as it needs to derive direct succession relations from traces of the original workflow [12].

Strategy 2 of ProR is more efficient than Strategy 1, though they are equivalent in deriving the optimal control flow graph. This is because fewer candidate subgraphs need to be considered by Strategy 2 for graph reduction. No matter which strategy is employed, ProR scales well with increasing DAG size. For instance, for the DAG with label “30”, although, it involves 85 activities and 84 edges, Strategy 1 and Strategy 2 of ProR take only 53.8 ms and 47.4 ms, respectively, to obtain the BPEL-like workflow models. The runtime overhead of ProR confirms the runtime complexity result of our approach.

The above experimental results demonstrate that ProR, not only guarantees obtaining workflow models with maximized concurrency and near-maximized block-structuredness, but also scales well in practice. Although other approaches may be slightly faster, the refactored workflows do either not exhibit maximized concurrency or are not as block-structured as possible.

6 Related Work

In this section, we review related studies on workflow anti-patterns [37], [5], [6], [7], [8], [15], workflow transformation [38], [39], [20], [40], [20], [41], [21], workflow refactoring [17], [16], [9], workflow enhancement based on workflow mining [42], [11], [12], [23], and draw a comparison between these studies and our work.

Workflow anti-patterns. We first review well-established workflow anti-patterns which are classified into two types [3]: control flow anti-patterns [37], [5], [6] and data flow anti-patterns [7], [8], [15]. Deadlocks and lack of synchronizations are two common kinds of control flow anti-patterns [37]. If an AND-join node is used to synchronize different branches of an XOR-split node, there will be a deadlock. If an XOR-join node is used to merge different threads of an AND-split node, the problem of lack of synchronization occurs because the XOR-join initializes more than once. Typical data flow anti-patterns includes missing input, redundant output, and lost output [7], [15]. Unoptimized sequence orders in executable workflows (e.g., BPEL processes) can be regarded as another type of anti-patterns which are related to the interplay of both the control flow and data flow [10].

Workflow transformation. Transforming unstructured workflow models into equivalent block-structured ones has been intensively studied [38], [39], [20], [40]. These studies focus on identifying kinds of unstructured workflows that can be transformed into structured equivalents. If this is not possible, maximal structuring of acyclic workflows is studied in [40]. However, the structuredness is achieved at the expense of duplicated nodes, where our approach does not require this. Besides, some researchers focus on more general situations, that is, transforming graph-based workflows into block-oriented workflows [20], [41], [21]. For example, Ouyang et al. study how to transform BPMN models to block-structured BPEL workflows [21]. Although existing studies closely relate to our work, there are three
main differences. First, since only control flow is considered and data flow is abstracted in these studies, they do not take concurrency maximization into account. Second, most of the work focuses on graph-based workflow models while our approach on BPEL-like models. Third, our approach focuses on deriving optimal control flow based on a dependence graph, whereas the above studies do not.

**Workflow refactoring.** A great deal of work focuses on improving the internal implementations of services without affecting the external observable behavior. For example, Ratkowski et al. in [17] propose a BPEL transformation approach to enhance the non-functional properties (e.g., performance, modifiability, granularity, and maintainability) of the original BPEL workflow but do not change its behaviour. Feng et al. leverage the data flow information to restructure service workflows [16]. Their goal is to improve the performance of service implementations while keeping the service protocol unchanged. Unfortunately, neither of these approaches discusses achieving maximized concurrency or block-structuredness. Ni et al. focus on detecting concurrency-relating problematic activity arrangements in BPEL workflows [9] and determine optimal control flow relations of a BPEL workflow. However, as we show in Section 5, their algorithm fails to maximizing concurrency.

**Workflow enhancement based on workflow mining.** Some recent work utilizes workflow mining (including Petri nets synthesis) techniques for workflow refactoring and enhancement. For instance, Wang et al. leverage the theory of regions and Petri nets synthesis to find the optimal representation of a service composition [11]. Jin et al. employ workflow discovery technique (i.e., the α-algorithm) to help reconstruct data-aware Petri nets [12]. The workflow mining approach presented in [23] can discover workflows from dependence-complete event logs. However, all these techniques can at most ensure maximized concurrency, while the block-structuredness is not considered. Leemans et al. propose a mining approach which can obtain block-structured workflow from a dependence graph (in terms of direct successorship relations) [42]. However, the process underlying the event log ought to be a tree structure. Our previous work [23] uses activity dependences for process discovery, which can derive a workflow model from the discovered dynamic dependence graph. However, this approach only considers local concurrency maximization while global concurrency maximization is not ensured.

### 7 Conclusions

In this paper, we have presented a refactoring approach to maximizing concurrency and block-structuredness for BPEL-like workflows. The main idea of our approach is to search in the workflow dependence graph for well-formed patterns whose control flow relations with maximized concurrency are block-structured. If a workflow cannot be fully block-structured, our approach uses synchronization links to make the refactored workflow near block-structured. Since the problem of introducing minimum links is intractable, we present a greedy algorithm to achieve efficiency. The experimental results on real-world scientific workflows demonstrate that our approach can efficiently obtain workflow models with maximized concurrency and few links. Our approach is also applicable to process discovery. Our future work will focus on other algorithms to introduce fewer links.

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