Modular Static Scheduling of Synchronous Data-flow Networks: An efficient symbolic representation *

Marc Pouzet [†]
LRI, Univ. Paris-Sud 11
INRIA
Orsay

Pascal Raymond[‡]
VERIMAG-CNRS
Grenoble

Abstract

This paper addresses the question of producing modular sequential imperative code from synchronous data-flow networks. Precisely, given a system with several input and output flows, how to decompose it into a minimal number of classes executed atomically and statically scheduled without restricting possible feedback loops between input and output?

Though this question has been identified by Raymond in the early years of LUSTRE, it has almost been left aside until the recent work of Lublinerman, Szegedy and Tripakis. The problem is proven to be intractable, in the sense that it belongs to the family of optimization problems where the corresponding decision problem — there exists a solution with size c — is NP-complete. Then, the authors derive an iterative algorithm looking for solutions for $c = 1, 2, ...$ where each step is encoded as a SAT problem.

Despite the apparent intractability of the problem, our experience is that real programs do not exhibit such a complexity. Based on earlier work by Raymond, this paper presents a new symbolic encoding of the problem in terms of input/output relations. This encoding *simplifies* the problem, in the sense that it rejects solutions, while keeping all the optimal ones. It allows, in polynomial time, (1) to identify nodes for which several schedules are feasible and thus are possible sources of combinatorial explosion; (2) to obtain solutions which in some cases are already optimal; (3) otherwise, to get a non trivial lower bound for c to start an iterative combinatorial search.

The solution applies to a large class of block-diagram formalisms based on atomic computations and a *delay* operator, ranging from synchronous languages such as LUSTRE or SCADE to modeling tools such as SIMULINK.

Terms: Algorithms, Languages, Theory.

Keywords: Real-time systems, Synchronous languages, Block-diagrams, Compilation, NP-completeness, Partial orders, Preorders.

1   Introduction

The synchronous block-diagram or *data-flow* formalism is now preeminent in a variety of design tools for embedded systems. Sequential code generation of synchronous block-diagrams have been considered in the early years of LUSTRE [7] and SIGNAL [1] and is provided by industrial tools such as SCADE [1] and RTBUILDER [2] for almost fifteen years. Though it has been considered more recently, modeling and simulation tools such as SIMULINK [3] and MODELICA [4] are now equipped with an automatic code generator.

We focus here on the problem of generating imperative, sequential code, implementing the functional behavior of a parallel data-flow network. We keep abstracted the (somehow orthogonal) problem of data

---

[1]http://www.esterel-technologies.com/scade/
[2]http://www.tni-software.com
[3]http://www.mathworks.com/product/simulink
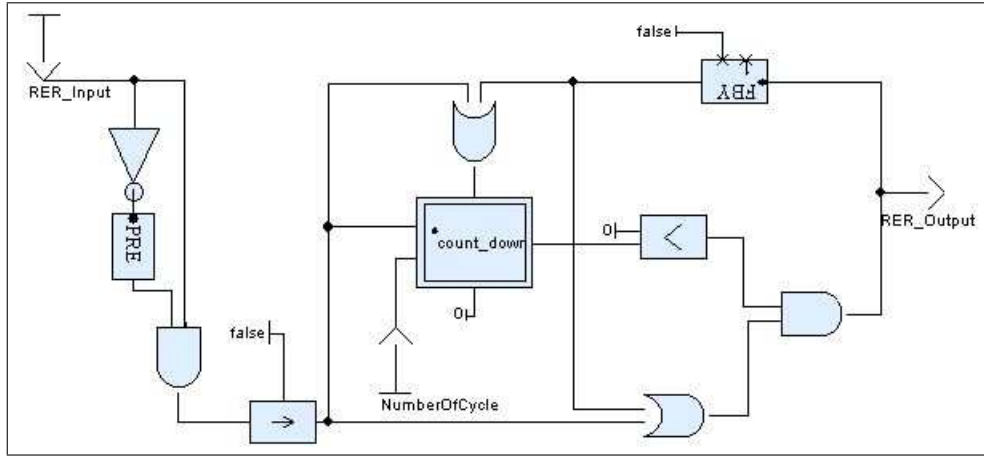[4]http://www.modelica.org

Figure 1: A SCADE (v5) block-diagram

management, that is, how values are actually passed from one node to another and even the interpretation of each operator. In particular, we address both data-flow networks with discrete-time (e.g., SCADE) or continuous-time (e.g., SIMULINK) semantics. Figure 1 gives an example of a SCADE block diagram and Figure 2, an example of a SIMULINK one.

Whatever be the semantics of nodes in a network, there are basically two types of atomic nodes. *Combinatorial* nodes need to evaluate all their arguments in order to produce their output. On the contrary, *delay* nodes are able to produce their output before reading their inputs. They correspond to unitary registers in synchronous designs (the so-called pre operator of LUSTRE), initialized buffers in Kahn process networks [9, 10] or continuous integrators in SIMULINK. Delays are essential to cut data-dependencies and to introduce well-founded feedback loops.

Given a system described as a data-flow network of atomic operators, code generation aims at producing a static schedule satisfying data-dependencies. This static schedule is feasible when there is no combinatorial loop, i.e., every loop in the graph crosses a delay. Data-flow formalism, just like any advanced programming language, allow the user to abstract his own programs into reusable components, that is, to build functions. This raises the problem of defining what is exactly a reusable parallel program, and how to compile it once for all into sequential code. Modular, or separate compilation, produces one piece of sequential code executed atomically for each function definition. Nonetheless, modular code generation is not always feasible even in the absence of combinatorial loops, as noticed by Gonthier [6]. If $copy(x, y) = (x + 1, y + 1)$ then the equation $(y, z) = copy(t, y)$ defines two perfectly valid streams y and z (since $y = t + 1$ and $z = y + 1 = (t + 1) + 1$) but it cannot be statically scheduled if $copy$ is compiled into one atomic step function. Indeed, it would make both y and z depend on t and y. This observation has conducted to two main compilation approaches. With the first one, or *white-boxing*, functions are statically inlined before code generation. This is the solution taken in the academic LUSTRE compiler. The opposite solution or *black-boxing*, keeps maximal code sharing by compiling each node individually into *one* code executed atomically. From the user point of view, such a node becomes a combinatorial node whatever are the internal dependencies between its input and output. As a consequence, every feedback loop must cross an explicit delay outside of the node. As is, this compilation method rejects causally correct programs (such as the *copy* example) which would have worked properly in a parallel execution or compiled with a white-box technique. This solution is the one taken in the compiler of SCADE and is combined to inlining *on demand* to accept all causally correct programs [3].

In this paper, we investigate an intermediate approach between the two that we call *grey-boxing*. It is based on the observation that some nodes are *compatible* in the sense that they can be executed together without restricting possible feedback loops between input and output. Then, the data-flow graph can be partitioned into a minimal number of classes, each of them executed atomically. This idea originally appeared in a work by Raymond published in a French report in 1988 [15]. Left aside, the subject has been reconsidered recently by Lublinerman and Tripakis. Their first proposal [13] was based on dynamic testing
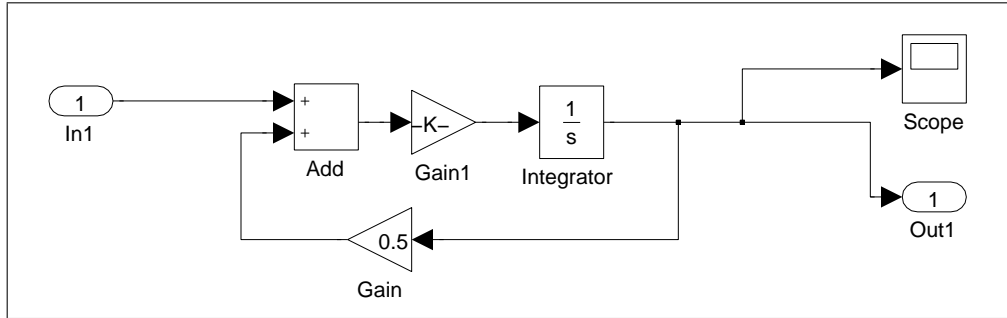
Figure 2: A SIMULINK block-diagram

to avoid the re-computation of shared values but, as they noticed in [12], this solution is costly in term of code size and execution time. In this recent work, Lublinerman, Szegedy and Tripakis come back to the original optimal static scheduling problem. They prove that the problem is intractable since it belongs to the family of optimization problems where the corresponding decision problem — is there a solution with at most c classes? — is NP-complete as it encodes the *clique cover* in a graph. Then, the authors derive an iterative algorithm looking for solutions for $c = 1, 2, ...$ where each step is encoded into a SAT problem.

Despite the apparent intractability of the problem, our experience is that real programs do not exhibit such a complexity. This calls for a careful look at the sources of combinatorial explosion and for an efficient encoding which limits this possible explosion. Moreover, we would like to build a polynomial test saying if a given instance of the problem can be polynomially solved or fall into the general case and call for an enumerative search. Based on earlier work by Raymond on a study of input/output relations, this paper proposes a symbolic and efficient representation of the problem. We show that this encoding *simplifies* the problem in the sense that it rejects solutions but keeps *all* the optimal ones. This symbolic representation allows, in polynomial time, (1) to identify nodes for which several schedules are feasible and thus are possible sources of complexity; (2) to obtain solutions which in some cases are already optimal; (3) otherwise, to get a non trivial lower bound for c to start an iterative combinatorial search, once the symbolic representation is translated into a boolean formula. All this is proven using basic properties of partial orders.

The paper is organized as follows. Section 2 presents the basics of the optimal scheduling problem and Section 3 develops the formalization. We start by giving another proof that optimal scheduling is intractable to help clarifying the sources of combinatorial explosion. In section 4, we present the symbolic representation based on input/output analysis, related properties and algorithms. Section 5 gives experimental results. We discuss related works in Section 6 and we conclude in section 7.

2 From Synchronous Data-flow to Relations

Consider the following synchronous data-flow program given below in LUSTRE syntax, and its corresponding block-diagram on the left side of Figure 3. The block NODE has two inputs a, b and two outputs x and y.

```
node NODE(a, b: t) returns (x, y: t);
  let
    x = j(a, f(D(a), b));
    y = h(b);
  tel;
```

There are essentially two kinds of operators in such a network, combinatorial and delay operators. Combinatorial ones (e.g., j, f and h) need their current input in order to produce their current output
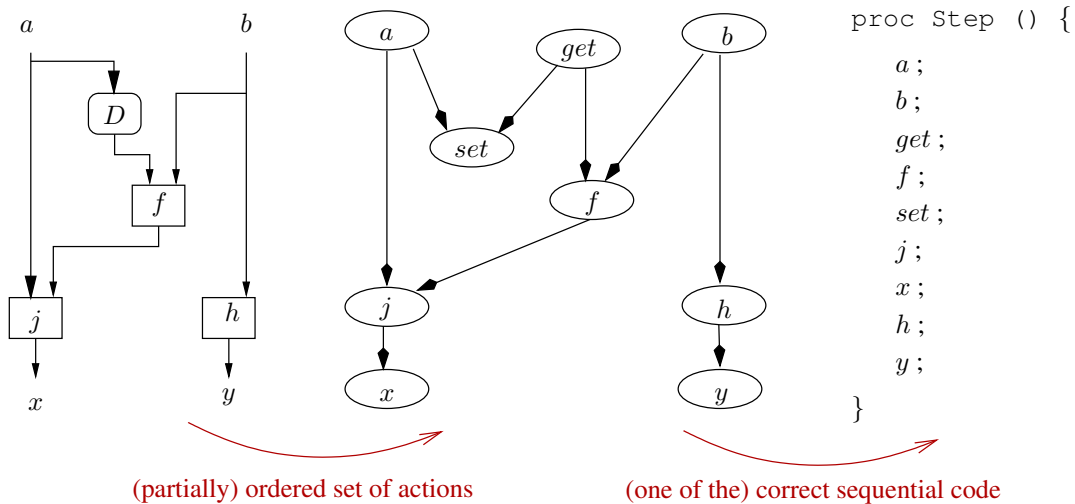
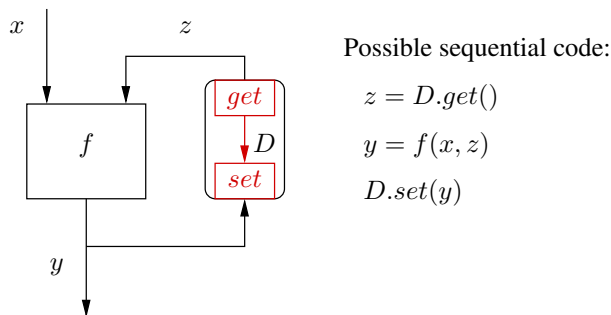Figure 3: A data-flow network and the corresponding ordered set of actions

Possible sequential code:

$$z = D.get()$$
$$y = f(x, z)$$
$$D.set(y)$$

Figure 4: The get/set principle breaks feedback loops

whereas a delay (e.g., `D`) is able to produce an output *before* it reads an input [5]. Delay nodes are used to program dynamical systems with feedback loops.

Focusing only on the scheduling problem of a data-flow network with delays — and not memory representation and optimization — the simplest way to represent a delay D is to express it as two atomic imperative actions $D.get$ and $D.set$. $D.get$ returns the current value of the delay whereas $D.set$ reads the current input and stores it for remaining execution. More importantly, if the result of $D.get$ is necessary, it must be executed before $D.set$ is executed. Said differently, a delay *reverses* the data-flow dependency between its input and its output and thus breaks cycles (Figure 4). Using this lower-level representation, data-flow networks we consider are simply partially ordered sets of atomic actions as defined below.

Definition 1 (Abstract Data-flow Networks) *A system $(A, I, O, \preceq)$ is made of:*

1. *a finite set of actions A,*

2. *a subset of inputs $I \subseteq A$,*

3. *a subset of output $O \subseteq A$ (not necessarily disjoint from I)*

4. *and a partial order $\preceq$ to represent precedence relation between actions.*

---

[5]The unitary delay is concretely written `pre` in LUSTRE and $1/z$ in (discrete) SIMULINK. From the dependencies point-of-view, an integrator ($1/s$) for a continuous signal in SIMULINK acts similarly.
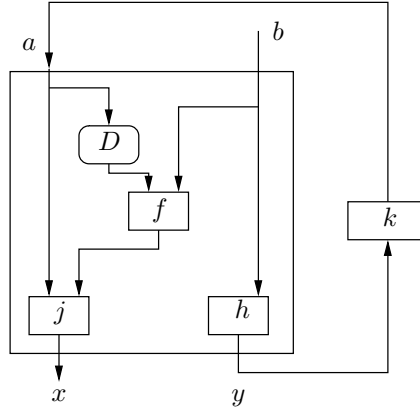
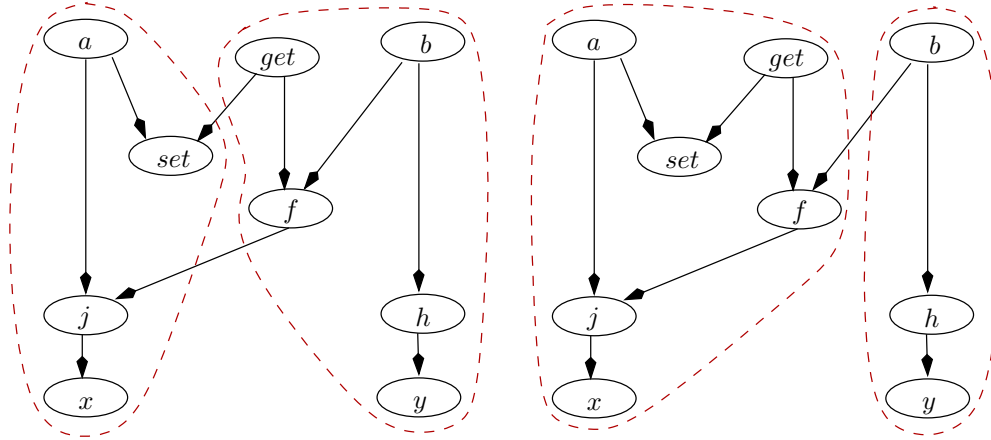Figure 5: A correct feedback use of a parallel component

Figure 6: Two possible "grey-boxing" and optimal scheduling

There is no constraint on I and O with respect to $\preceq$. In particular, one may have $x \preceq i$ or $o \preceq x$ with $x \in A$, $i \in I$ and $o \in O$.

In the following, the static scheduling problem of a concrete data-flow program is considered only on this representation. The encoding from one to the other is not detailed.

Figure 3 shows a block-diagram (left) and the corresponding ordered set of actions (center). The delay node D is replaced by the corresponding actions set and get. Note that only the direct dependencies are shown, the partial order is, as usual, the transitive closure of the represented acyclic graph. From this partially ordered set, code generation mainly consists in finding a correct scheduling for the actions, that is, a total order including the partial dependency order. One of the correct scheduling is shown on the right side of Figure 3.

In such a network, it makes sense to feedback an output to an input as soon as the output does not depend combinatorially on this input. We say that such a feedback is causality correct. This is illustrated by the example of Figure 5. If we allow such an external loop, it is not possible to use a single, monolithic code, such as the one given in the left of Figure 3: in any correct sequence, the computation of the external node k must take place between the computations of the internal nodes h and j. However, it is clear that it is not necessary to externalize the code of each node in the graph, that is, to inline `NODE`. Some nodes can be gathered without preventing causally correct feedback loops. The static scheduling problem is to generate the minimal number of classes of compatible nodes. For example, f can be computed:

- together with h, as soon as b is provided;

5

```
proc P1 () {
    b ;
    get ;
    f ;
    h ;
    y ;
}
proc P2 () {
    a ;
    set ;
    j ;
    x ;
}
P1 before P2
```

Block P2   Block P1

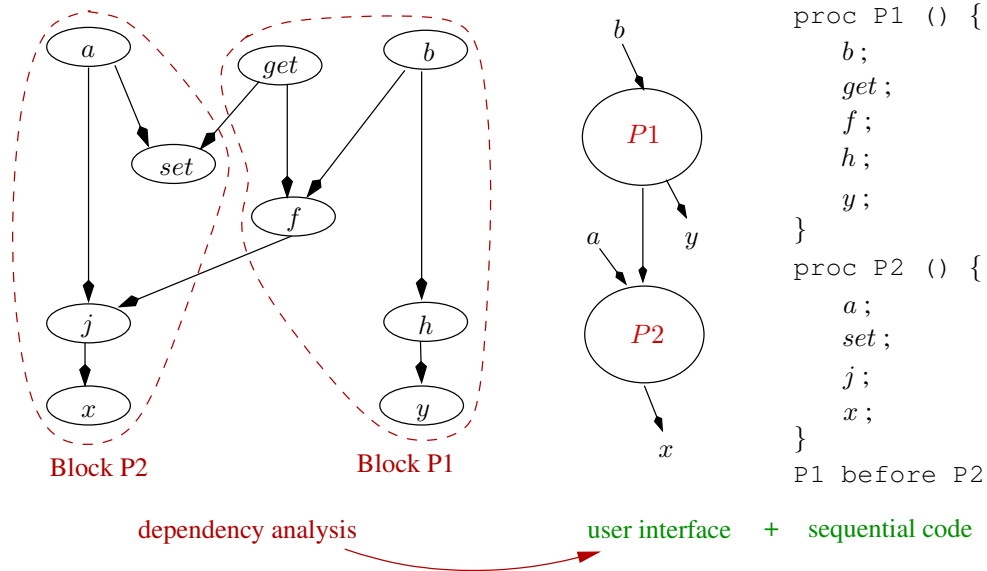dependency analysis   user interface   +   sequential code

Figure 7: Grey-boxing: orderer blocks plus sequential code

- together with (and before) j in order to provide the output x.

The same reasoning holds for the delay D:

- $D.get$ is clearly associated to the computation of f;

- $D.set$ requires the input a, and for this reason, is related to the action j.

Finally, this intuitive reasoning shows that the node can be abstracted into two atomic pieces of code:

- the class for h with input b and output y;

- the class for j with input a, output x, and which must always be computed after the class for h.

However, the frontier between these two classes is not strict: some internal computations can be performed on one side or the other, e.g., g and f. Figure 6 shows two particular optimal solutions in the number of classes. Once these blocks have been identified, we can compile each of them into sequential code executed atomically and export them together with the relative dependence constraints. From the caller, NODE is now seen as a data-flow graph with two actions — the class of h and the class of j. The call to NODE is replaced with a call to the two associated functions. Figure 7 summarizes this principle, a optimal partition of the actions is chosen (left), from which one can derive the interface and the dependencies between the two blocks (center) and the actual sequential code for each block (right).

Note that the formulation with $(A, I, O, \preceq)$ is fully modular and enough to address the static scheduling problem. At each level of the hierarchy, we can focus on a set of actions, some of them being inputs and/or outputs and some being local. We now formalize the grey-boxing problem.

3   Formalization

3.1   Optimal Static Scheduling

Let A be a set of actions, partially ordered by $\preceq$, and two subsets of A, $I \subseteq A$ (input nodes) and $O \subseteq A$ (output nodes).

Definition 2 (Compatibility) *Two actions $x, y \in A$ are said to be (static-scheduling) compatible and this is written $x \chi y$ when the following property holds:*

$$x \chi y \stackrel{def}{=} \forall i \in I, \forall o \in O, ((i \preceq x \wedge y \preceq o) \Rightarrow (i \preceq o)) \ \wedge \ ((i \preceq y \wedge x \preceq o) \Rightarrow (i \preceq o))$$

Incompatibility is the property which formalizes the fact that two nodes (either internal, input or output) can not be statically scheduled within the same piece of atomic code: if two actions are not compatible (for instance $i \preceq x$, $y \preceq o$ and $i \npreceq o$), it is possible to feedback o to the input i without introducing a combinatorial loop. Thus, setting x and y together into the same piece of code would make this feedback impossible.

The goal is to find classes of pairwise compatible actions in A. Note that compatibility is not a solution, since it is not an equivalence. It is symmetric, reflexive, but not transitive in general: for example, in Figure 6, $f \chi j$ and $f \chi b$ hold but not $j \chi b$.

Moreover, not any equivalence $\simeq$ included in χ is a solution: the atomic blocks must be made of pairwise compatible actions, but they must also be schedulable with respect to $\preceq$, without introducing any extra dependencies between input and output.

In other terms, we are looking for an equivalence relation plus a (partial) order over the classes. This is strictly equivalent to search a *preorder* (reflexive, transitive, not symmetric relation) over the set of actions.

Definition 3 (Optimal Static Scheduling (OSS)) *A static schedule is a relation $\precsim \ \subseteq \ A \times A$ such that:*

- *(SS-0) $\precsim$ is a* preorder *(reflexive, transitive), and we note $\simeq$ the underlying equivalence relation ($x \simeq y \ \Leftrightarrow \ x \precsim y \ \wedge \ y \precsim x$),*

- *(SS-1) $x \preceq y \Rightarrow x \precsim y$ (it contains all the dependency constraints),*

- *(SS-2) $\forall i \in I, \forall o \in O, \ \ i \precsim o \ \Leftrightarrow \ i \preceq o$ (the preorder strictly maps the dependency on input/output pairs).*

Moreover, a static schedule is said optimal (OSS) if it satisfies the following property:

- *(SS-3) $\simeq$ is maximal (i.e. it has a minimal number of classes).*

Property 1 *The main property following the definition SS-0 to SS-2 is that the equivalence $\simeq$ associated to a static scheduling $\precsim$ is a subset of the compatibility relation:*

- *(SS-prop) $x \simeq \ y \Rightarrow x \ \chi \ y$*

Proof: Let $\precsim$ be a static scheduling, suppose that it exist some actions x, y, input i and output o such that $x \simeq \ y$, $i \preceq x$, $y \preceq o$ and $i \npreceq o$, by SS-1, $i \precsim x$ and $y \precsim o$, then, since (in particular) $x \precsim y$, $i \precsim o$ and by SS-2 $i \preceq o$, which is absurd.

3.2 Theoretical Complexity of OSS

An equivalent definition of the problem, presented in terms of graphs and clusters, has been proposed in [12]. Authors have shown that it is NP-hard, through a reduction of the *partition in k cliques* problem, also known as *clique cover* [5].

Even if it is not new, we briefly present here an alternative encoding which leads to the same result. This encoding is interesting since it helps to understand why the problem is theoretically hard, while being simple on small but typical systems such as the one given in Figure 6.

We show that any *minimal clique cover* problem can be linearly encoded into a OSS instance. First, we reformulate the problem in terms of relations: given a finite set L and a symmetric relation $\leftrightarrow$ (i.e. a non oriented graph), find a maximal equivalence relation $\simeq$ included in $\leftrightarrow$ (i.e. with a minimal number of classes, called cliques in the original formulation).

This problem has indeed many similarities with OSS since OSS mainly consists in finding a maximal equivalence included in a symmetric relation (the compatibility). However, it is not trivial that compatibility relations can be as general as symmetric relations.
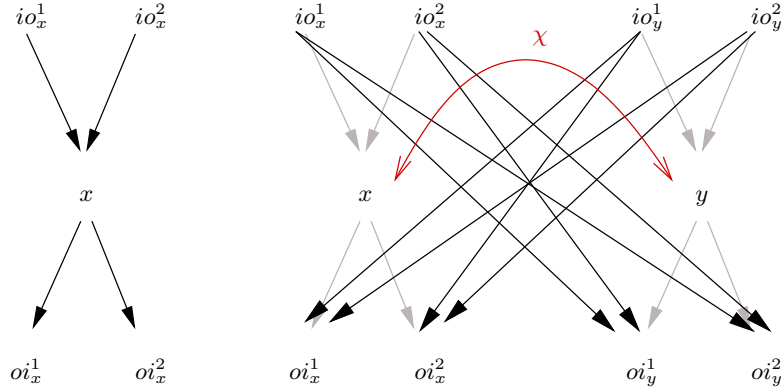
Figure 8: The X-encoding, isolated node (left), and related pair (right)

The X-encoding   In order to prove it, we propose an encoding of MCC into OSS, called X-encoding (*cross*-encoding).

Let $G = (L, \leftrightarrow)$ be the data of a MCC problem. We build a OSS instance with an extra set of nodes X: $(A = L \uplus X, I = O = X, \preceq)$ (i.e. each extra variable is both an input and an output), in the following way:

1. For each $x \in L$, we introduce 4 extra variables io_x^1, io_x^2, oi_x^1 and oi_x^2 that are *both* input and output. Each local variable x and its extra input/output variables are related by the dependency relation in a "X" (cross) shape, as presented on the left side of Figure 8.

2. For each pair x, y such that $x \leftrightarrow y$, we add 8 dependencies by connecting each input of x to each output of y and vice versa, as shown on the right side of Figure 8.

The X-encoding ensures that each additional node (io_x^1, io_x^2, oi_x^1 and oi_x^2) is incompatible with any other variables. For instance, an extra variable io_x^1 is incompatible:

- with any other extra variable of type io or oi, since it can be fed back to any of them,

- with any local node $y \neq x$, since it can be fed back either to io_y^1 or io_y^2,

- with the associated local variable x since it can be fed back to the other extra input io_x^2.

The same reasoning applies for variables of type oi.

The dependencies added for each pair $x \leftrightarrow y$ enforce that x is compatible with y: all outputs of y depend on all inputs of x and reciprocally. On the contrary, if $x \not\leftrightarrow y$, no extra dependencies are introduced and $x \not\chi y$: any output of x can be fed back to any input of y and reciprocally.

Finally, we have $x \chi y \iff x \leftrightarrow y$. Note that it establishes that a compatibility relation can be an arbitrary symmetric relation.

MCC is equivalent to OSS via X-encoding

1. Let $\simeq$ be a solution of the clique cover problem over $(L, \leftrightarrow)$ and consider the relation R over $(L \cup X, \preceq)$ which is the *transitive closure* of the relation $\simeq \cup \preceq$. This relation:

   - is a preorder (SS-0),

   - by definition, it contains $\preceq$ (SS-1),

   - it does not add any extra dependency between inputs and outputs (SS2).
     Proof: Firstly, note that "inputs" (nodes of type io), are minimal by construction for both $\simeq$ and $\preceq$, and then, the transitive closure cannot introduce any relation between two nodes of type io. The same reasoning holds for "outputs" (type oi) which are maximal by construction. As a consequence, the transitive closure necessarily passes through internal nodes.
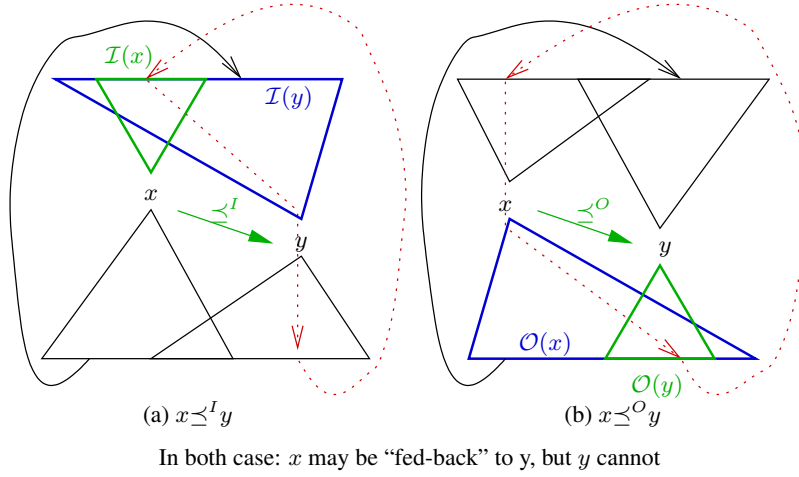
(a) $x{\preceq}^I y$ (b) $x{\preceq}^O y$

In both case: x may be "fed-back" to y, but y cannot

Figure 9: Pre-orders $x{\preceq}^I y$ and $x{\preceq}^O y$ give extra information on feasible scheduling.

Secondly, since by construction $x{\not\simeq}y$ for any pair of internal nodes, $x\,R\,y$ is necessarily due to the transitive closure of $\simeq$, wich is, by definition already transitive, thus: $x\,R\,y \iff x\simeq y$.

Now, suppose that is exists an input/output pair such that $i\,R\,o$ and $i{\not\preceq}o$; then it exists two internal nodes x,y such that $i{\preceq}x$, $x\,R\,y$, and $y{\preceq}o$, but $x\,R\,y \iff x\simeq y$, and, since $\simeq$ is a solution of the clique cover, $x\simeq y \implies x{\leftrightarrow}y$. Finally, we have $i{\preceq}x$, $y{\preceq}o$ and $x{\leftrightarrow}y$, and then, because of the X-encoding construction (left side of Figure 8), $i{\preceq}o$, which is absurd.

2. Let $\stackrel{\sim}{\preceq}$ be a solution of the X-encoded problem over $(L \cup X, \preceq)$ and $\simeq$ the associated equivalence. Since $\simeq \subseteq \chi$ and χ only concerns internal nodes, then $\simeq$ is also an equivalence over L and thus, a solution of the clique-cover problem.

3. Moreover, an optimal solution for one problem necessarily gives an optimal solution for the other: suppose, for instance, that $\simeq$ is an optimal solution of the clique cover, and that the transitive closure R of $\simeq \cup \preceq$ is not an optimal scheduling. Then it exists a strictly better scheduling $\stackrel{\sim}{\preceq}$ from which we can derive, by (2), a solution of the clique cover which is strictly better than the optimal: this is absurd.

A main interest of this encoding is that it suggests that, even if OSS is proven to be at least as complex as MCC, the instances of OSS that are supposed to be computationally hard are far from what is a typical data-flow program: in order to fit the general case, we have to consider programs where the number of inputs/outputs is larger than the number of internal nodes, an uncommon situation in practice.

Our purpose is to establish that the complexity of OSS is strongly related to the number of inputs/outputs, and the structure of their dependencies.

4 Input/Output Analysis

This section shows that the OSS problem can be reformulated, and in some sense *simplified*, by analyzing the relations between input and output.

4.1 Input/Output Saturation

Let $(A, I, O, \preceq)$ be a data-flow network.

Comparing the sets of inputs (resp. outputs) of two nodes may give information on how they can be statically scheduled without forbidding valid feedbacks. Let $\mathcal{I}(x)$ be the input variables on which x depends on. Let $\mathcal{O}(x)$ be the output variables depending on x. As shown in Figure 9:

- (a) if the inputs $\mathcal{I}(x)$ of x are included in the inputs $\mathcal{I}(y)$ of y, then any feedback from an output of y to some input of x creates a combinatorial loop. As a consequence, it is never the case that y *should be computed* before x. In other words, x can always be computed before y. We write $x {\preceq}^I y$.

- (b) the same reasoning holds with the (reverse) inclusion of outputs: if $\mathcal{O}(x) \supseteq \mathcal{O}(y)$ then x can always be computed before y. We write $x {\preceq}^O y$.

These relations ${\preceq}^I$ and ${\preceq}^O$, that are trivially preorders, are called respectively the *input* (resp. *output*) saturations of the relation $\preceq$. They are solutions of SS:

- (SS-1) they both include $\preceq$, since $x {\preceq} y$ implies $\mathcal{I}(x) \subseteq \mathcal{I}(y)$ and $\mathcal{O}(x) \supseteq \mathcal{O}(y)$,

- (SS-2) they do not introduce any extra input/output dependency, since $\mathcal{O}(i) \supseteq \mathcal{O}(o)$, and, in particular, $o \in \mathcal{O}(o)$, we have $i \preceq o$ (similarly for the inclusion of input).

It follows that, from the basic dependency relation (which is a non optimal solution of SS), one can derive another solution which is still non optimal, but better than the original.

In what have been defined above, we have build ${\preceq}^I$ and ${\preceq}^O$ starting from the data-dependence relation $\preceq$ which is already a valid solution to the static scheduling problem. In fact, the same reasoning holds when starting from any preorder which is a solution of SS.

Definition 4 (Input and output saturation) *Given a solution $\precsim$ of the SS problem, we define its input (resp. output) function, saturation preorder and equivalence:*

$$
\begin{aligned}
\mathcal{I}^{\precsim}(x) &= \{i \in I, i {\precsim} x\} \\
x {\precsim}^I y &\Leftrightarrow \mathcal{I}^{\precsim}(x) \subseteq \mathcal{I}^{\precsim}(y) \\
x {\simeq}^I y &\Leftrightarrow \mathcal{I}^{\precsim}(x) = \mathcal{I}^{\precsim}(y) \\
\mathcal{O}^{\precsim}(x) &= \{o \in O, x {\precsim} o\} \\
x {\precsim}^O y &\Leftrightarrow \mathcal{O}^{\precsim}(x) \supseteq \mathcal{O}^{\precsim}(y) \\
x {\simeq}^O y &\Leftrightarrow \mathcal{O}^{\precsim}(x) = \mathcal{O}^{\precsim}(y)
\end{aligned}
$$

We list the main properties of the saturation preorders, and detail the proof only for the input-saturation ${\precsim}^I$ (the case of ${\precsim}^O$ is dual):

Property 2 ${\precsim}^I$ *and* ${\precsim}^O$ *are solutions of SS.*

Proof for ${\precsim}^I$:

- (SS-1) since $\precsim$ is itself a solution of SS, $x {\precsim} y \Rightarrow x {\precsim} y$, and $x {\precsim} y \Rightarrow \mathcal{I}^{\precsim}(x) \subseteq \mathcal{I}^{\precsim}(y)$

- (SS-2) if $\mathcal{I}^{\precsim}(i) \subseteq \mathcal{I}^{\precsim}(o)$ then, since in particular $i \in \mathcal{I}^{\precsim}(i)$, we have $i {\precsim} o$, which implies $i \preceq o$ since $\precsim$ satisfies SS-3

The same reasoning applies for ${\precsim}^O$.

Property 3 *for any SS solution, input-saturation equivalence equals compatibility on outputs, and output-saturation equivalence equals compatibility on inputs:*

$$
\begin{aligned}
\forall o, o' \in O \quad & o {\simeq}^I o' \Leftrightarrow o \chi o' \\
\forall i, i' \in I \quad & i {\simeq}^O i' \Leftrightarrow i \chi i'
\end{aligned}
$$

Proof for ${\simeq}^I$: For all output o, o',

- $o {\simeq}^I o' \Rightarrow o \chi o'$, because of SS-prop,

- in order to prove the converse, since χ is symmetric, we simply prove that $o \chi o' \Rightarrow o {\precsim}^I o'$.

  If $o {\not\precsim}^I o'$, then it exists $i \in I$ such that $i {\precsim} o$ and $i {\not\precsim} o'$, from SS-2, we have also $i \preceq o$ and $i \not\preceq o'$, and then o and o' are not compatible.

The same reasoning applies for ${\simeq}^O$.

Property 4 *In any optimal solution of SS, two inputs (resp. outputs) that are compatible are necessarily in the same class.*

Proof for output pairs:

- Suppose that $\precsim$ is an optimal solution of SS, where two compatible outputs are not equivalent ($o \not\simeq o'$) then compute its input-saturation $\simeq^I$.

- From the properties of $\simeq^I$, $o\simeq^I o'$, and then $\simeq^I$ and $\simeq$ are different. Moreover $\simeq^I$ is greater or equal ($\simeq^I \supseteq \simeq$) than $\simeq$.

- Finally, $\simeq^I$ has strictly less classes than the supposed optimal solution, which is absurd.

The proof is similar for input pairs.

Indeed, saturation works only once: let $\precsim$ be a SS solution and $\precsim^I$ its input-saturation, then the property $i\precsim^I x \Leftrightarrow i\precsim x$ holds: input according to $\precsim^I$ are exactly output according to $\precsim$. The same reasoning applies for the output-saturation.

However, performing input-saturation then output-saturation (or the reverse) may give some extra information.

Definition 5 (Input/output preorder) *Let $\precsim$ be a solution of SS, we define its input/output saturation $\precsim^{Io}$, and equivalence $\simeq^{Io}$, as the input-saturation of its output-saturation:*

$$
\begin{aligned}
\mathcal{I}_{\mathcal{O}}^{\precsim}(x) &= \{i \in I , i\precsim^O x\} \\
x\precsim^{Io}y &\Leftrightarrow \mathcal{I}_{\mathcal{O}}^{\precsim}(x) \subseteq \mathcal{I}_{\mathcal{O}}^{\precsim}(y) \\
x\simeq^{Io}y &\Leftrightarrow \mathcal{I}_{\mathcal{O}}^{\precsim}(x) = \mathcal{I}_{\mathcal{O}}^{\precsim}(y)
\end{aligned}
$$

This preorder inherits from the properties of both saturations:

1. It is a solution of SS,

2. it meets the compatibility relation on inputs ($i\chi i' \Leftrightarrow i\simeq^{Io} i'$),

3. it meets the compatibility relation on outputs ($o\chi o' \Leftrightarrow o\simeq^{Io} o'$).

Moreover, it has a new property on input/output pairs:

Property 5 $\simeq^{Io}$ *meets compatibility on $I \times O$:*
$$\forall i \in I, \forall o \in O, i\chi o \ \Leftrightarrow i\simeq^{Io}o$$

Proof:

- $i\simeq^{Io}o$ implies $i\chi o$ from SS-prop.

- $i\chi o \Rightarrow i\precsim o$ by definition, $i\precsim o \Leftrightarrow i\precsim^{Io}o$ from SS-2.

- $i\chi o \Rightarrow o\precsim^{Io}i$, because, if $o\not\precsim^{Io}i$ it exists i' such that (a) $i'\precsim^O o$ and (b) $i'\not\precsim^O i$; from (a) and SS-2 $i'\precsim o$ and from (b) $\exists o'\ i\precsim o' \ \wedge \ i'\not\precsim o'$, thus, from SS-2, i and o are not compatible.

The consequence of these properties is that, in any optimal solution of the SS problem, any pair of compatible nodes in $I \cup O$ are necessarily in the same equivalence class.

Moreover these equivalence classes on $I \cup O$ can be computed from any known solution of SS, in particular from the trivial "worst" solution $\preceq$. We note $\mathcal{I}_{\mathcal{O}}$ and $\preceq^{Io}$ the input-output function and saturation of $\preceq$.

In other words, there is no choice for "clustering" inputs and outputs in an optimal solution. Moreover, computing $\mathcal{I}_{\mathcal{O}}$ gives a lower bound to the number of classes. However, there remain several problems to address: where to put local nodes in an optimal solution? When additional classes are necessary? How many additional classes are necessary?

Our purpose in the sequel is to precise and solve these problems, while trying to identify simple cases for which the optimal solution can be given in polynomial time from the "hard" ones, that fall into the NP-hard theoretical complexity.

4.2 Static Scheduling as a Mapping in the Input Power-set

In this section, we show that solving (O)SS is equivalent to finding a (minimal) mapping of the actions into the power-set of inputs [6]. Consider a mapping $\mathcal{K} : A \mapsto 2^I$, which satisfies the following properties:

- (KI-1) $\forall x \in I \cup O, \ \ \mathcal{K}(x) = \mathcal{I}_\mathcal{O}(x)$

- (KI-2) $\forall x, y, \ \ x \preceq y \ \Rightarrow \ \mathcal{K}(x) \subseteq \mathcal{K}(y)$

The problem of finding a mapping satisfying these properties is called the *Keys as inputs subsets* encoding (or KI-enc). Obviously, the dual problem of *Keys as outputs* is equivalent. We show that this problem solves the SS one, in the sense that a solution of KI-enc directly leads to a solution of SS.

KI-enc solves SS: Indeed, the mapping $\mathcal{I}_\mathcal{O}$ is a trivial solution of KI-enc, and it gives, through keys inclusion, a solution of SS which is simply $\preceq^{I_O}$. The result is nonetheless much more general: let $\mathcal{K}$ be any solution of KI, then the preorder $x \precsim y \Leftrightarrow \mathcal{K}(x) \subseteq \mathcal{K}(y)$ is a solution of SS:

- SS-1 follows from KI-2,
- SS-2 follows from KI-1 and the properties of $\mathcal{I}_\mathcal{O}$.

SS solves (and is improved by) KI-enc: suppose that $\precsim$ is a solution of SS, apply output and then input saturation, the corresponding $\mathcal{I}_\mathcal{O}^{\precsim}$ is a solution of KI-enc, and, moreover the corresponding preorder is equal or better (i.e. included) than $\precsim$.

These properties are interesting for the search of optimal solutions, that is, preorders with a minimum number of classes. They imply that (1) any solution of KI-enc gives a solution of SS, (2) from any solution of SS, one can build a *better or identical* solution of KI-enc. In other terms, the KI-enc formulation has strictly less solutions than SS, but it does not miss *any optimal solution*.

4.3 Computing the KI-enc System

We reformulate here the KI-enc problem into a more computational problem. First, it is not necessary to compute explicitly the dependency order $\preceq$. We rather suppose that this order is implicitly given by a direct acyclic graph $\rightarrow$, linearly deduced from the wires in the original data-flow program (e.g. given in SCADE or SIMULINK). Finaly, we consider a graph $(A, I, O, \rightarrow)$:

- where A is a set of n nodes (actions),

- I is the subset of n_i inputs,

- O is the subset of n_o outputs,

- $\rightarrow \in A \times A$ is a dependency graph of p arcs, whose transitive closure is the dependency (partial) order $\preceq$. We do not require this graph to be minimal: the only interesting property is that is size p is linear with respect of the original program.

We build a system of (in)equations with a variable K_x for each $x \in A$:

- $K_x = \mathcal{I}_\mathcal{O}(x)$ for $x \in I \cup O$

- $\bigcup\limits_{y \rightarrow x} K_y \ \subseteq \ K_x \ \subseteq \ \bigcap\limits_{x \rightarrow z} K_z$ otherwise

Where $\bigcup$ and $\bigcap$ are the natural n-ary extensions of union and intersection, that is, they map 0-argument to their respective neutral element: $\bigcup\limits_\emptyset = \emptyset$, and $\bigcap\limits_\emptyset = I$.

---

[6] All the definition and properties we give can be replayed, by computing instead a mapping into the power-set of outputs.

Complexity analysis   The complexity of building the KI-enc system from a graph $(A, I, O, \rightarrow)$ is mainly due to the computation of $\mathcal{I}_\mathcal{O}$:

- computing the output function $\mathcal{O}$ can be done by assigning to each node a set variable O_x, and then by visiting once, in a bottom-up topological order, the n nodes and p arcs of the dependency graph. For each arc $x \rightarrow y$, a set union must be made ($O_x := O_x \cup O_y$) whose cost is theoretically in $n_o \cdot \log n_o$ (negligible, in practice, for small values of n_o when sets are encoded as bit-vectors). The global cost is of the order $n + p \cdot n_o \cdot \log n_o$.

- given $\mathcal{O}$, the $\mathcal{I}_\mathcal{O}$ of each node x can be computed by comparing $\mathcal{O}(x)$ to $\mathcal{O}(i)$ (cost in $n_o \cdot \log n_o$), if it is included, i is added to the known $\mathcal{I}_\mathcal{O}$ of x (cost in $\log n_i$). The cost is globally of the order $n \cdot n_i \cdot \log n_i \cdot n_o \cdot \log n_o$,

Finally, the system can be built in (roughly) $z \cdot m^2 \cdot (\log m)^2$, where $z = n + p$ characterizes the size of the graph, and $m = max(n_i, n_o)$ characterizes the size of its interface.

If we isolate the costs of set operations ($B(m)$ for binary ones, and $A(m)$ for insertion), we obtain the expression $z \cdot m \cdot B(m) \cdot (m)$ which gives a more interesting information in practice: the cost is mainly the size of the graph times the size of its interface times the cost of set operation.

Iterating SAT searching   The system of set inequations is trivially a SAT problem, since a subset of I can be represented by a vector of n_i booleans:

- each variable K_x can be encoded by a vector of Boolean variables $[K_x^1, \cdots, K_x^{n_i}]$

- each constant $\mathcal{I}_\mathcal{O}(x)$ can be replaced by the corresponding vector of n_i bits,

- $\bigcup$ is the bitwise logical or, $\bigcap$ is the bitwise logical and.

As we have shown in section 4.1, the system outlines the fact that some classes are necessary: the ones corresponding to the $\mathcal{I}_\mathcal{O}$ of inputs and outputs. We call them the c mandatory classes $M_1, ... M_c$. An optimal solution can be obtained by iterating SAT-solver calls:

- search a solution with $c + 0$ classes, by adding, for each local variable x, the constraint $\bigvee_{j=1}^{j=c}(K_x = M_j)$, and calling a SAT solver,

- if it fails, search for a solution with $c + 1$ classes, i.e., introduce a new *vector of n_i free variables S_1* and add this variable vector as a new possible value for each local x:
$$\bigvee_{j=1}^{j=c}(K_x = M_j) \vee (K_x = S_1)$$

- if it fails, introduce another extra variable S_2, and so on.

However, before applying a costly iterative search, it is interesting to study more precisely the system itself and its sources of complexity.

4.4   Simplifying the KI-enc System

Lower and higher bounds   For each variable, we define the lower and the upper solution:

- $k_x^\perp = k_x^\top = \mathcal{I}_\mathcal{O}(x)$ for $x \in I \cup O$

- $k_x^\perp = \bigcup_{y \rightarrow x} k_y^\perp$ and $k_x^\top = \bigcap_{x \rightarrow z} k_z^\top$ otherwise.

It is easily shown that $k_x^\top$ is in fact $\mathcal{I}_\mathcal{O}(x)$: setting all variables to their upper bound corresponds to the already known solution $\preceq^{I_\mathcal{O}}$. It corresponds to the heuristic "schedule as late as possible" and we call this solution $\mathcal{K}^\top$. Dually, choosing $K_x = k_x^\perp$ for each node is also a solution which corresponds to the heuristic "schedule as soon as possible" and we call this solution $\mathcal{K}^\perp$. These two solutions are *a priori* nor comparable nor optimal in general. However, if it appears that all $k_x^\top$ (respectively $k_x^\perp$) are keys of
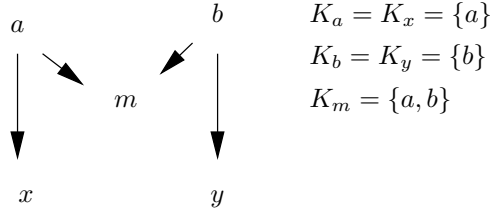
$$K_a = K_x = \{a\}$$
$$K_b = K_y = \{b\}$$
$$K_m = \{a, b\}$$

Figure 10: A simple "M" shape, where $I = \{a, b\}$ and $O = \{x, y\}$.

$$K_a = K_z = \{a\}$$
$$K_b = K_t = \{b\}$$
$$K_c = K_x = \{a, b, c\}$$
$$K_d = K_y = \{a, b, d\}$$
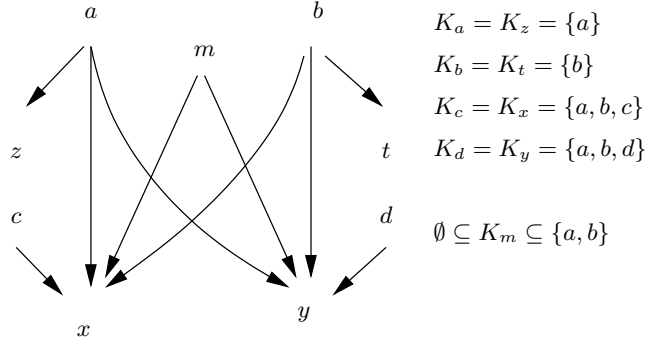$$\emptyset \subseteq K_m \subseteq \{a, b\}$$

Figure 11: A "M/W" shape, where $I = \{a, b, c, d\}$ and $O = \{x, y, z, t\}$.

mandatory classes (i.e. keys of some input or output), we can already conclude that $\mathcal{K}^\top$ (respectively $\mathcal{K}^\perp$) is an optimal solution.

In some cases, the bounds may give the optimal solution: whenever $k_x^\perp = k_x^\top$, the inequation becomes an equation and the class becomes mandatory even if it not the class of any input or output. This situation happens when it is easy to decide if some purely internal class is necessary. This is illustrated in figure Figure 10: the local node m must be computed alone in a class that should be scheduled after the class of a and the class of b.

Bounds reduction The bounds can be introduced into the inequalities, whose general form is then:

$$k_x^\perp \cup \bigcup_{y \to x} K_y \ \subseteq \ K_x \ \subseteq \ k_x^\top \cap \bigcap_{x \to z} K_z$$

For any $y \to x$ such that $k_y^\top \subseteq k_x^\perp$, the constraint $K_y \subseteq K_x$ is redundant and can be removed; similarly for any $x \to z$ such that $k_x^\top \subseteq k_z^\perp$. This simplification is called the (redundant) bounds reduction. With this reduction, it may appear than all variables are removed in an inequation, and thus, some variables become bounded by constants:

$$k_x^\perp \ \subseteq \ K_x \ \subseteq \ k_x^\top$$

Whenever $k_x^\perp \neq k_x^\top$ for some x, there are several choices for the position of x within the static schedule, that may lead or not to an optimal solution. Figure 11 shows a small example with a "M/W" shape where the position of the local variable m is bounded by two constants. In this case, no extra class is necessary if the intersection of all the intervals contains a mandatory class. In this example, the answer is trivial since we have only one interval. It includes both the mandatory classes $\{a\}$ and $\{b\}$ and one can choose either $K_m = \{a\}$ or $K_m = \{b\}$ to obtain an optimal solution.
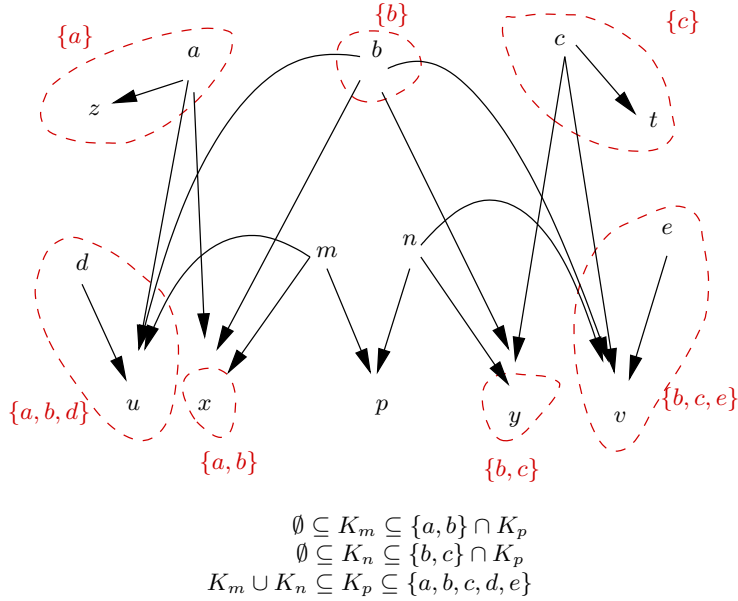
$$\emptyset \subseteq K_m \subseteq \{a, b\} \cap K_p$$
$$\emptyset \subseteq K_n \subseteq \{b, c\} \cap K_p$$
$$K_m \cup K_n \subseteq K_p \subseteq \{a, b, c, d, e\}$$

Figure 12: A generalized "M/W" shape, where $I = \{a, b, c, d, e\}$ and $O = \{x, y, z, t, u, v\}$.

As soon as there are more than 3 such variables, we fall in a case that is equivalent to the one of the X-encoded problem: n independent internal variables have to be organized in a minimum number of classes, according to their bounds.

The problem is even more complex when the bounds are not constant: the position of some local variable may depend on the position of another and so on. Figure 12 illustrates this case by generalizing the "M/W" shape. Several optimal choices can be made, that do not require extra classes, for instance $K_m = K_n = K_p = \{b\}$, but also $K_m = \{a\}, K_n = \{b\}, K_p = \{a, b\}$ and more. But these optimal solutions cannot be obtained by considering variables one by one. For instance, $K_m = \{a\}$ is locally a good choice, such as $K_n = \{c\}$; but once these two choices have been made, there is no solution for p other than $K_p = \{a, c\}$ which obliges to introduce a extra class. When several variables are related, they must be considered "all together", making the problem computationally hard.

As a conclusion, the proposed encoding may, in some cases, directly give solutions that are proven optimal and, otherwise, it exhibits the parts of the systems that are *real* sources of complexity. This appears when the system still contains inequations whose lower and upper bounds are different and involve other variables.

5 Experimentation

We have developed a prototype implementation in OCAML [11] to experiment with the ideas presented previously. Two kind of examples have been considered: a collection of relatively small programs taken from the SCADE library and two real-size industrial applications from Airbus. Through not particularly optimized (e.g., all set operations being implemented with the standard OCAML library), the prototype requires respectively 2, 0.5 and 10 seconds on a laptop (centrino 1.2 Ghz, running Linux Debian) to treat the whole 3 benchmarks presented here.

For every SCADE (or LUSTRE) code, the dependency information is extracted and the KI-system is build. It is checked whether:

- it is only made of equations, in which case the system is solved by simple propagation of facts. We call it the *trivial* case.

- it still contains inequalities but either all the upper bounds or all the lower bounds in the inequalities

SCADE libs	trivials	solved	others
n. of programs (155)	41	114	0
n. of classes	1	1 to 2	-
n. of in/out	2 to 5	2 to 9	-
n. of nodes	2 to 18	8 to 64	-
av. size	10	24	-

Bench 2	trivials	solved	others
n. of programs (27)	8	19	0
n. of classes	1	1 to 4	-
n. of in/out	2 to 10	2 to 19	-
n. of nodes	2 to 29	9 to 48	-
av. size	14	20	-

Bench 3	trivials	solved	others
n. of programs (125)	39	85	1
n. of classes	1 to 3	1 to 4	3 or 4
n. of in/out	2 to 14	2 to 26	4+2
n. of nodes	7 to 350	12 to 600	25
av. size	50	80	-

Results show the ranges of the number of classes (i.e. the size of the optimal solution); the programs in a particular benchmark are of various sizes, we give the ranges of the number of inputs/outputs and of internal nodes, and also the average size (in internal nodes).

Figure 13: Experimental results: almost 100% of the programs are polynomially solved.

are mandatory, that is, they appear in some equations. In this case, either $\mathcal{K}^\top$ or $\mathcal{K}^\perp$ are proven to be optimal solutions. The system is called *solved*. It corresponds to the situation where a simple heuristic — always compute as soon as possible or always compute as late as possible — gives an optimal solution.

- otherwise, the system is considered to be *complex*. It contains equations that give a set of mandatory classes. It also contains inequations but some upper bounds and some lower bounds are not mandatory. Thus, neither $\mathcal{K}^\top$ nor $\mathcal{K}^\perp$ are proven to be optimal. As we have presented in 4.3, the tools generates a generic Boolean formula parameterized by the number of extra classes ec. This formula can be expanded for $ec = 0, 1, ...$ and then given to a Boolean solver.

Benchmark 1 (Scade Lib) The problem of modular compilation is clearly interesting for programs that are supposed to be reusable. This is why we have chosen, as a first benchmark, the libraries of the SCADE tool [7]. The benchmark is made of 155 block diagrams (we simply call them programs in the sequel), which are indeed relatively small. Not surprisingly, none of them was identified as *complex* (see Figure 13). Moreover, 88% of the programs are combinatorial: every output depends on all inputs (this is the case for the mathematical libraries, for example). As a consequence they trivially require a single computation block. The other operators (19 over 155) are basic temporal operators (e.g. integrators) which require two blocks.

Since it seems very unlikely to find complex reusable programs, we have tried to apply the method on bigger industrial examples.

Benchmark 2 This benchmark is extracted from a medium industrial application from Airbus. We have extracted 27 components and sub-components of a medium sized application (about 600 atomic nodes

---

[7]For practical reasons, we have used the libraries of the version 4.2

```
{ }  <= K(g1)  <=  {d, a}
{a} <= K(v10) <=  {d, a}                    K(v3)  <= K(s0)
{a} <= K(s1)  <=  {d, c, b, a}              K(v3)  <= K(v4)
{ }  <= K(g0)  <=  {a}                       K(v9)  <= K(v11)
{ }  <= K(v2)  <=  {a}                       K(v10) <= K(s1)
{ }  <= K(v9)  <=  {d, a}                    K(v10) <= K(v11)
{a} <= K(v11) <=  {d, a}                     K(g0)  <= K(v2)
{a} <= K(v3)  <=  {c, b, a}                  K(g1)  <= K(s1)
{a} <= K(s0)  <=  {d, c, b, a}               K(g1)  <= K(v9)
{a} <= K(v4)  <=  {c, b, a}
```

Figure 14: System of inequations of a (possibly) complex program, as it is echoed by the prototype: the constants bounds (left) and the variables constraints (right).

when flattened). Indeed, performing modular compilation is not really relevant in this case since the components are not intended to be reused. But the goal here is to experiment the method on programs that are relatively bigger than those that can be found in libraries. Finally, the conclusion is the same as in the first benchmark: all the programs are solved by a simple input/output analysis. One particular program is interesting: it has 11 inputs and 4 outputs for a total of 30 nodes, and its optimal static scheduling has 4 classes, which is for the time being a (very relative) top of complexity.

Benchmark 3   The last benchmark is also extracted from an Airbus application, but it is bigger than the previous one: 125 components are extracted from an application whose flat size is about 8000 nodes. Once again, the components are rather tasks and sub-tasks than reusable operators, and they are not obviously candidates for separate compilation.

The conclusion is the same as before except that we have found a program that is not *solved* (cf. column *others* in the last table of Figure 13). This program has 24 nodes, 4 inputs and 2 outputs, the minimal number of (mandatory) classes is 3, and both $\mathcal{K}^\top$ and $\mathcal{K}^\perp$ give 4 classes. The corresponding system of equations is simplified and the tool isolates 10 internal variables whose position is not clear. Figure 14 shows the bounds and the remaining inter-dependencies of these variables.

It appears that, in fact, this is also a simple problem, but it requires a heuristic that is not yet implemented in the prototype:

- the intersection of all the intervals is not empty ($\{a\}$);

- moreover, the class $\{a\}$ is one of the 3 mandatory classes;

- thus, setting all the variables to $\{a\}$ satisfies all the constraints without introducing any extra classes.

Conclusion   Is it possible indeed to build an arbitrarily huge and complex data-flow network, e.g., by multiplying the "M/W" shape given in Figure 12. However, our experience is that hand-written data-flow networks are rather "simple", in particular because the number of inputs/outputs of a program is relatively small with respect to the number of internal nodes.

If it is admitted that modular compilation is useful — a problem which is briefly discussed in the next section —, the proposed approach consists in using an *inexpensive* algorithm that:

- in most cases, gives an optimal solution;

- identifies the problem as being potentially "hard" and calls a third-party non-polynomial tool for solving it.

6   Discussion and Related Works

Various approaches to the code generation problem of synchronous data-flow diagrams have been experimented in compilers.

Modular Code Generation Modular code generation, as followed by the SCADE compiler, essentially translates every stream function into a single function [3]. This way, modules can be compiled separately, calling conventions (to build libraries or to link synchronous code with others) are almost trivial and this simplifies traceability issues between the source and target code. It appears that extra constraints imposed on feedback loops are well accepted by users [8]. Combined with partial inlining, all remaining causally correct programs are accepted. Note that in tools such as SCADE (but it also applies to SIMULINK), many functions are local as they are only used to structure the code: they are not exported to build libraries and are only instantiated once. Any good compiler always inlines these functions thus reducing again the set of functions that need a decomposition into classes. A classical variation of the unique transition function is to split it in two, one to produce the output and one to modify the state [9]. In the case of a node where its outputs do not depend on its input (as for the delay node), this solution allows to compile modularly an extra set of programs but it is incomplete (e.g., it fails to compile the example given in begining of section 2).

This black-boxing approach to code generation was almost discarded in the LUSTRE compiler as it may reject causally correct programs. Programs are compiled after a full inlining of functions and this allows to generate efficient automata [8].

Optimal Static Scheduling The question of decomposing a data-flow graph into classes has been also studied by Benveniste & al. for the compilation of SIGNAL and was observed to be similar to the problem of code distribution [2]. It is formulated for a more expressive model of conditional scheduling constraints: a relation $x \xrightarrow{ck} y$ states that that "when ck is true, y must be executed after x". A graph can be scheduled when all cycles $x_1 \xrightarrow{ck_1} x_2 \xrightarrow{ck_2} ...x_1$ are such that $\neg(ck_1 \wedge ... \wedge ck_n)$. We thus have considered the case where the ck_i are true. Nonetheless, the question of producing an optimal solution in number of classes does not seem to have been addressed.

We have already pointed the main differences with the work of Lublinerman, Szedezy and Tripakis [12]. The optimal solution is obtained iteratively for $c = 1, 2, ...$ with a general solution based on a SAT encoding of a decomposition into c classes. Nonetheless, real programs have simple dependency relations and can be treated with a dedicated algorithm with mastered worst-case complexity. In most applications we have found, the optimal is obtained in polynomial time using the direct algorithm based on the input/output relations. Even in the case where an iterative search would have to be done, it allows to start with a non trivial lower bound for c.

Input/Output Analysis *vs* Direct Boolean Encoding Since programs are *simple* in practice, one may argue that there is no much difference in actual cost between a direct boolean encoding of the OSS problem such as [12] and a dedicated algorithm. We could expect that each SAT problem — there exist a solution with c classes — is easy to solve and the number of iterations for c to stay small.

Nonetheless the behavior, and thus, the cost, of the SAT solving is hard to predict, whereas the presented algorithm answers in polynomial time whether the **KI-enc** is solved or not. In the small remaining cases where an enumerative search is necessary (if an optimal solution is expected), the algorithm starts from a non trivial minimal number of mandatory classes. In several benchmarks, this minimal number of classes was greater than 1.

Finally, is not clear that finding an optimal solution is central in practice. In all the examples we have treated $\mathcal{K}^\perp$ and/or $\mathcal{K}^\top$ allows to obtain either the optimal solution or a solution close to the optimal.

7 Conclusion

This paper addressed the static scheduling problem of a synchronous data-flow network to be used in a compilation chain into sequential code. Precisely, how to decompose a data-flow network into a minimal

---

[8]This is also due to the nature of applications written in SCADE where closed loops are programmed to be robust to the insertion of a delay.

[9]This approach is convenient when the code is linked to a numerical variable step solver as it simplifies the rollback mechanism.

number of classes executed atomically without restricting possible feedback loops between input and output? Though this optimization problem is intractable in the general case and must be tackled with general combinatorial methods, our experience is that real programs do not reveal such a complexity. This calls for a specific algorithm able to identify programs which can be solved in polynomial time. Based on the notion of input/output properties, we build a symbolic representation (keys as inputs subsets, or KI-enc) of the problem. This representation *simplifies* the problem in the sense that it has strictly less solutions but it contains *all* optimal ones. This representation gives a non trivial lower bound on the number of classes, and two particular solutions $\mathcal{K}^{\perp}$ and $\mathcal{K}^{\top}$. It can then be checked whether $\mathcal{K}^{\perp}$ and/or $\mathcal{K}^{\top}$ are optimal or not by comparing their number of classes with the lower bound. In most programs we have encountered, $\mathcal{K}^{\perp}$ is optimal. Otherwise, the non trivial bound on the number of classes is used to start a combinatorial search with a SAT-solver.

Acknowledgments

References

[1] A. Benveniste, P. LeGuernic, and Ch. Jacquemot. Synchronous programming with events and relations: the SIGNAL language and its semantics. *Science of Computer Programming*, 16:103–149, 1991.

[2] Albert Benveniste, Paul Le Guernic, and Pascal Aubry. Compositionality in dataflow synchronous languages: Specification & code generation. Technical Report R3310, INRIA, November 1997.

[3] Darek Biernacki, Jean-Louis Colaco, Grégoire Hamon, and Marc Pouzet. Clock-directed Modular Code Generation of Synchronous Data-flow Languages. In *ACM International Conference on Languages, Compilers, and Tools for Embedded Systems (LCTES)*, Tucson, Arizona, June 2008. Extended version of [4].

[4] Darek Biernacki, Jean-Louis Colaco, and Marc Pouzet. Clock-directed Modular Compilation from Synchronous Block-diagrams. In *Workshop on Automatic Program Generation for Embedded Systems (APGES)*, Salzburg, Austria, october 2007. Embedded System Week.

[5] M. R. Garey and D. S. Johnson. *Computers and Intractability - A guide to the Theory of NP-completeness*. Freeman, New-York, 1979.

[6] Georges Gonthier. *Sémantiques et modèles d'exécution des langages réactifs synchrones*. PhD thesis, Université Paris VI, Paris, 1988.

[7] N. Halbwachs, P. Caspi, P. Raymond, and D. Pilaud. The synchronous dataflow programming language LUSTRE. *Proceedings of the IEEE*, 79(9):1305–1320, September 1991.

[8] N. Halbwachs, P. Raymond, and C. Ratel. Generating efficient code from data-flow programs. In *Third International Symposium on Programming Language Implementation and Logic Programming*, Passau (Germany), August 1991.

[9] Gilles Kahn. The semantics of a simple language for parallel programming. In *IFIP 74 Congress*. North Holland, Amsterdam, 1974.

[10] E. A. Lee and D. G. Messerschmitt. Static scheduling of synchronous data flow programs for digital signal processing. *IEEE Trans. on Computers*, 36(2), 1987.

[11] Xavier Leroy. The Objective Caml system release 3.11. Documentation and user's manual. Technical report, INRIA, 2009.

[12] R. Lublinerman, C. Szegedy, and S. Tripakis. Modular Code Generation from Synchronous Block Diagrams — Modularity vs. Code Size. In *ACM Principles of Programming Languages (POPL)*, 2009.

[13] R. Lublinerman and S. Tripakis. Modularity vs. reusability: Code generation from synchronous block diagrams. In *Design, Automation and Test in Europe (DATE'08)*, 2008.

[14] Marc Pouzet and Pascal Raymond. Modular static scheduling of synchronous data-flow networks: An efficient symbolic representation. In *ACM International Conference on Embedded Software (EM-SOFT'09)*, Grenoble, France, October 2009.

[15] Pascal Raymond. Compilation séparée de programmes lustre. Technical report, Projet SPECTRE, IMAG, july 1988. http://www-verimag.imag.fr/SYNCHRONE/publis/spectre-L5.pdf.