A Constraint Functional Logic Language for Solving Combinatorial Problems

Antonio J. Fernández*
Lenguajes y Ciencias de la Computación, Universidad de Málaga
Málaga, Spain

Teresa Hortalá-González†, Fernando Sáenz-Pérez†
Sistemas Informáticos y Programación, Universidad Complutense de Madrid,
Madrid, Spain

Abstract

We present CFLP(FD), a constraint functional logic programming approach over finite domains (FD) for solving typical combinatorial problems. Our approach adds to former approaches as Constraint Logic Programming (CLP), and Functional Logic Programming (FLP) both expressiveness and further efficiency by combining combinatorial search with propagation. We integrate FD constraints into the functional logic language TOY. CFLP(FD) programs consist of TOY rules with FD constraints declared as functions. CFLP(FD) seamlessly combines the power of CLP over FD with the higher order characteristics of FLP.

1 Introduction

Declarative programming (DP) is intended to separate the problem formulation from the procedure to solve the problem itself. Well-known DP instances are logic programming (LP) on which the problem can be expressed in first-order predicate calculus and functional programming (FP) that allows to express problems in terms of higher order functions. Recently, constraint logic programming (CLP) emerged to increase both the expressiveness and efficiency of LP programs [9]. The basic idea in CLP consists of replacing the classical LP unification by constraint solving on a given computation domain. Then, different instances of the computation domain generate different CLP instances that are used in the solving of problems of distinct nature.

Among the domains for CLP, the Finite Domain (FD) [6] is one of the most and best studied since it is a suitable framework for solving discrete constraint satisfaction problems. The importance of the CLP languages based on FD is in their impact in the industry since a lot of problems in the real life involve variables ranging on discrete domains. Unfortunately, literature lacks proposals

*E-mail: afdez@lcc.uma.es. The work of this author was partially supported by the project TIC2001-2705-C03-02 funded by the Spanish Ministry of Science and Technology.

†E-mails: {teresa,fernan}@sip.ucm.es. The work of these authors has been supported by the Spanish project PR 48/01-9901 funded by UCM.

to integrate FD constraints in the functional setting. This seems to be caused by the relational nature of the FD constraints that do not fit well in FP.

Another instance of DP is functional logic programming (FLP) that emerges with the aim to integrate the declarative techniques used in both FP and LP and that gives rise to new features not existing in FP or LP [5]. This paper describes our work of integrating FD constraints as functions in the FLP language TOY [10, 11], which includes pure LP and lazy FP programs as particular cases. Our work is a contribution for further augmenting the expressive power of FLP by adding the possibility of solving FD constraint problems in the functional logic setting. As far as we know, there is no concrete realization of a pure F(L)P language embodying FD constraints. In this paper, we show the integration of FD constraints into a FLP language.

The structure of the paper is as follows: Section 2 shows our implementation of CFLP(FD). Section 3 highlights some advantages obtained from integrating constraints into a functional logic language. Section 4 introduces some program examples which show how to benefit from the integration of FLP and FD. Finally, section 5 summarizes some conclusions and points out future work.

2 TOY(FD) : a CFLP(FD) Implementation

This section describes part of TOY(FD), that is, our CFLP(FD) implementation that extends the TOY system to deal with FD constraints and that also shows how to increase the FLP paradigm by integrating FD constraints as functions. This implementation uses the efficient SICStus Prolog FD library [2]. (For a more detailed description of TOY and TOY(FD) see [10] and [4].)

2.1 Constraints as Functions

TOY(FD) provides support for six different categories of FD constraints: (1) relational constraints, (2) arithmetic constraints, (3) combinatorial constraints, (4) membership constraints, (5) enumeration constraints, and (6) statistics constraints. For reasons of space, we only briefly describe part of these categories.

Assume L, L_1, L_2 are lists (vectors) of integers and/or FD variables with length n; X, Y, N are either FD variables or integer values; V, V_1, V_2 are integers and *RelOp* is a value that represents a relational operator. Suppose also that $equiv(RelOp)$ is a function that returns the classical arithmetic operator equivalent to the value *RelOp* (i.e., $equiv(lt)$ is '#<', $equiv(eq)$ is '#=', $equiv(le)$ is '#<=', $equiv(ge)$ is '#>=', $equiv(gt)$ is '#>' and $equiv(neq)$ is '#\=').

Relational Constraints include equality and disequality constraints in the form $e \diamond e'$ where $\diamond \in \{\#<, \#=, \#<=, \#>=, \#>, \#\backslash=\}$ and e and e' are either integers, or FD variables or functional expressions.

Arithmetic Constraints include all the classical arithmetic operators as well as the dedicated constraints 'sum/3' and 'scalar_products/4' where

- '*sum L RelOp V*' is true if $\left(\sum_{\mathbf{e} \in \mathbf{L}} \mathbf{e}\right)\ equiv(RelOp)\ \mathbf{V}$ holds.

- '*scalar_products* L_1 L_2 *RelOp* V' is true if the scalar product of L_1 and L_2 is related with the value V by the operator *RelOp*, i.e., if

$$L_1 \ *_s \ L_2 \ equiv(RelOp) \ V$$

  is satisfied with $*_s$ defined as the usual scalar product of integer vectors.

As expected, the expressions constructed from both the arithmetic and relational constraints may be non-linear.

Combinatorial Constraints include well-known global constraints that are useful to solve problems defined on discrete domains. For example,

- '*assignment*/2' is applied over two lists of domain variables with length n where each variable takes a value in $\{1, \ldots, n\}$ which is unique for that list. Then, '*assignment* L_1 L_2' is true if for all $i, j \in \{1, \ldots, n\}$, and $X_i \in L_1$, $Y_j \in L_2$, then $X_i = j$ if and only if $Y_j = i$.
- '*all_different* L' and '*all_distinct* L' are true if each variable in L is constrained to have a value that is unique in the list L and there are no duplicate integers in the list L, i.e., this is equivalent to say that for all $X, Y \in L$, $X \neq Y$. The difference between both constraints is that *all_different*/1 uses a complete algorithm that maintains the domain consistency whereas *all_distinct*/1 uses an incomplete one. There are extended versions that allow one more argument which is a list of options, where each option may have one of the following values
  1. 'on value', 'on domains' or 'on range' to specify that the constraint has to be woken up, respectively, when a variable becomes ground, when the domain associated to a variable changes, or when a bound of the domain (in interval form) associated to a variable changes.
  2. 'complete true' or 'complete false' to specify if the propagation algorithm to apply is complete or incomplete.
- '*circuit* L_1' and '$circuit'$ L_1 L_2' are true if the values in L_1 form a Hamiltonian circuit. This constraint can be thought of as constraining n nodes in a graph to form a Hamiltonian circuit where the nodes are numbered from 1 to n and the circuit starts in node 1, visits each node and returns to the origin. Also the i-th element of L_1 (resp. L_2) is the successor (resp. predecessor) of i in the graph.
- '*element* X L Y' is true if the X-th element in the list L is Y.
- '*count* V L *RelOp* Y' is true if the number of elements of L that are equal to V is N and also N *equiv*(*RelOp*) Y (in the sense of FD).

Membership Constraints restrict variables to have values in a set of integers (i.e., an interval). The expression '*domain* L V_1 V_2' is true if each element in the list L belongs to the interval $[V_1, V_2]$.

Enumeration Constraints reactivate the search process when no more constraint propagation is possible. TOY(FD) provides the following constraints:

1. '*indomain X*' that assigns a value, from the minimum to the maximum in its domain, to X.

2. '*labeling Options L*' that is true if an assignment of the variables in L can be found such that all of the constraints are satisfied. *Options* is a list of four elements that allow to specify the nature of the search.

3 Advantages of the Integration

3.1 Semantic Advantages

FLP languages express problems as higher order functions with logic variables, which allows one-way expression reduction. Also, in functional languages, relations cannot be expressed. However, constraint programming languages allow to express relations with a pure declarative reading (so that multi-way uses of the variables in the relation can be applied, i.e., different modes for the variables: input or output). The integration therefore allows expressing relations involving logic variables combined with functional applications.

3.2 Operational Advantages

Solving in logic programming languages (including functional logic) is based on different techniques including SLD resolution (logic programming), narrowing, and residuation (functional logic programming). These languages feature the concept of logic variable. A logic variable is assigned only once to at most a unique value during the search for a solution (a computation branch). Due to their nondeterminism, several solutions may exist (and, therefore, several computation branches). The multiset of solutions is characterized by all the sets of possible assignments for each variable in the goal during the computation[1]. The search space is the union of all the computation branches. Nondeterminism provides the way to formulate combinatorial problems since alternatives for rules (in FLP) or clauses (in LP) may provide different assignments to the same variable. Combinatorial problems can therefore be expressed with such languages, but an exhaustive enumerative procedure is implicitly used for the search of solutions.

Also, solving in constraint systems is based on constraint propagation and labeling. The first prunes the search space by reducing domains, and the second finds solutions by assigning values to variables.

A constraint system starts solving by propagating the effects of the constraints over the domains of variables. This means that, in general, propagation implies that each current domain will decrease its cardinality (pruning). There are several propagation algorithms in the literature which behave differently and may reach different fixed points. The fixed point is reached whenever there is no further domain reduction. These algorithms implement an iterative procedure which looks for a stable situation (fixed point), or a failure (a domain

[1]Several computation branches may lead to the same solution due to redundant alternatives.

becomes empty, i.e., there is no possibility of finding an assignment for the related variable such that all the constraints are satisfied). Finding a fixed point with non-singleton domains does not mean that there are definitely multiple solutions to the problem, and it does not even ensure that at least one solution exists. Propagation is not complete in the sense of ensuring the existence of solutions. Instead, it is used to find out what assignments definitely do not lead to a solution. The premise in this approach is to identify in advance, as soon as possible, what partial solution (where not all domains are singletons) is not a solution before trying to assign all the variables. Note that this follows a different approach than those from the enumeration techniques, which try to find solutions by simultaneously assigning values to all the variables, so that one knows that a solution is found when all variables have been assigned.

Once propagation procedure reaches a fixed point and at least one domain is not a singleton, labeling can be initiated in order to find feasible assignments. Indeed, the search for solutions could be seen at this point from an enumeration point of view. However, each time a variable is assigned to a value, propagation can be started until a fixed point had been reached. Next, a new assignment can be made, a new propagation cycle started, and so on, until a solution is computed or not found. The latter means that backtracking must be started in order to find another possible assignment. Each time a variable is labeled (assigned to a value among the possible values in its domain), a choice point must be annotated in order to try different assignments through backtracking.

Solving in a (constraint logic) system embodying logic variables, an enumerative search procedure (as those for LP and FLP), and a constraint solving procedure (propagation and labeling), allows to constrain variable domains during the enumerative search, therefore hopefully identifying a failure in advance (before the assignment of the variable). This improves efficiency since computation branches are pruned in advance with the information given by the constraints. In addition, lazy narrowing may avoid computations which are not demanded, therefore saving computation time.

Moreover, CFLPFD constraints are declared as functions so that a wrong use can be straightforwardly detected in the typical type checking process (in FLP) a priori, before execution. Therefore, this saves time in both correcting and debugging programs.

4 Programming in TOY(FD)

Any CLP(FD)-program can be straightforwardly translated into a CFLP(FD)-program so that CLP(FD) may be considered an instance of CFLP(FD) what determines a wide range of applications for our language. We will not insist here on this matter, but prefer to concentrate on the extra capabilities of the language. We illustrate here different features of CFLP(FD) by means of examples. We would like to emphasize that all the pieces of code are executable in TOY(FD) and the answers for example goals correspond to actual execution of the program.

4.1 A Scheduling Problem

Here, we consider the problem of scheduling tasks that require resources to complete, and have to fulfill precedence constraints. Figure 1 shows a precedence graph for six tasks which are labeled as tX^{Y}_{mZ}, where X stands for the identifier of a task t, Y for its time to complete (duration), and Z for the identifier of a machine m (a resource needed for performing task tX).

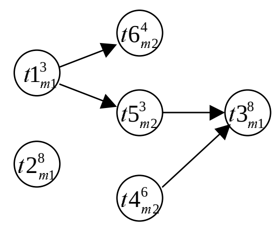

Figure 1: Precedence Graph.

The following program models the posed scheduling problem. Observe in the syntax that function arguments are not enclosed in parentheses to allow higher order applications. Also, syntactic sugar is provided for expressing Boolean functions à la Prolog. The rules that define a function follow its type declaration. The type declaration consists of the types for each argument and for the result separated by `->`. Lists adhere to the syntax as Prolog lists and **int** is a predefined type for the integers. Note also functional applications in arguments, such as `(End-D)` in the 2nd rule defining `horizon`. (Logic) Variables start with uppercase, whereas the remaining symbols start with lowercase.

```
data taskName = t1 | t2 | t3 | t4 | t5 | t6
data resourceName = m1 | m2
type durationType = int
type startType = int
type precedencesType = [taskName]
type resourcesType = [resourceName]
type task=(taskName,durationType,precedencesType,resourcesType,startType)

start :: task -> int
start (Name, Duration, Precedences, Resources, Start) = Start

duration :: task -> int
duration (Name, Duration, Precedences, Resources, Start) = Duration

schedule :: [task] -> int -> int -> bool
schedule TL Start End :- horizon TL Start End, scheduleTasks TL TL

horizon :: [task] -> int -> int -> bool
horizon [] S E = true
horizon [(N, D, P, R, S)|Ts] Start End :-
    domain [S] Start (End-D), horizon Ts Start End
```

```
scheduleTasks :: [task] -> [task] -> bool
scheduleTasks [] TL = true
scheduleTasks [(N, D, P, R, S)|Ts] TL :-
    precedeList (N, D, P, R, S) P TL,
    requireList (N, D, P, R, S) R TL,
    scheduleTasks Ts TL

precedeList :: task -> [taskName] -> [task] -> bool
precedeList T [] TL = true
precedeList T1 [TN|TNs] TL :-
    belongs (TN, D, P, R, S) TL, precedes (TN, D, P, R, S) T1,
    precedeList T1 TNs TL

precedes :: task -> task -> bool
precedes T1 T2 = (start T1) #+ (duration T1) #<= (start T2)

requireList :: task -> [resourceName] -> [task] -> bool
requireList T [] TL = true
requireList T [R|Rs] TL :- requires T R TL, requireList T Rs TL

requires :: task -> resourceName -> [task] -> bool
requires T R [] = true
requires (N1, D1, P1, R1, S1) R [(N2, D2, P2, R2, S2)|Ts] :-
    N1 /= N2, belongs R R2,
    noOverlaps (N1, D1, P1, R1, S1) (N2, D2, P2, R2, S2),
    requires (N1, D1, P1, R1, S1) R Ts
requires T1 R [T2|Ts] :- requires T1 R Ts

belongs :: A -> [A] -> bool
belongs R [] = false
belongs R [R|Rs] = true
belongs R [R1|Rs] = belongs R Rs

noOverlaps :: task -> task -> bool
noOverlaps T1 T2 :- precedes T1 T2
noOverlaps T1 T2 :- precedes T2 T1
```

A task is modeled (via the type `task`) as a 5-tuple which holds its name, duration, list of precedence tasks, list of required resources, and the start time. Two functions for accessing the start time and duration of a task are provided (`start` and `duration`, respectively) that are used by the function `precedes`. This last function imposes the precedence constraint between two tasks. The function `requireList` imposes the constraints for tasks requiring resources, i.e., if two different tasks require the same resource, they cannot overlap. The function `noOverlaps` states that for two non overlapping tasks $t1$ and $t2$, either $t1$ precedes $t2$ or vice versa. The main function is `schedule`, which takes three arguments: a list of tasks to be scheduled, the scheduling start time, and the maximum scheduling final time. These last two arguments represent the time window that has to fit the scheduling. The time window is imposed via domain pruning for each task's start time (a task cannot start at a time so that its duration makes its end time greater than the end time of the window; this is imposed with the function `horizon`). The function `scheduleTasks` imposes the precedence and requirement constraints for all of the tasks in the scheduling. Precedence constraints and requirement constraints are imposed by the functions `precedeList` and `requireList`, respectively.

With this model, we can submit the following goal, which defines the set of tasks, and asks for a possible scheduling in the time window (1,20):

```
Tasks == [(t1,3,[],[m1],S1), (t2,8,[],[m1],S2),   (t3,8,[t4,t5],[m1],S3),
          (t4,6,[],[m2],S4), (t5,3,[t1],[m2],S5), (t6,4,[t1],[m2],S6)],
schedule Tasks 1 20, labeling [] [S1,S2,S3,S4,S5,S6]
```

4.2 A More Involved Example

A more interesting example comes from the hardware arena. In this setting, many constrained optimization problems arise in the design of both sequential and combinational circuits as well as the interconnection routing between components. Constraint programming has been shown to effectively attack these problems. In particular, the interconnection routing problem (one of the major tasks in the physical design of very large scale integration - VLSI - circuits) have been solved with constraint logic programming [12].

For the sake of conciseness and clarity, we focus on a constraint combinational hardware problem at the logical level but adding constraints about the physical factors the circuit has to meet. This problem shows some nice features of TOY for specifying issues such as behavior, topology and physical factors.

Our problem can be stated as follows. Given a set of gates and modules, a switching function, and the problem parameters maximum circuit area, power dissipation, cost, and delay (dynamic behavior), the problem consists of finding possible topologies based on the given gates and modules so that it meets the switching function and it commits to the constraint physical factors.

In order to have a manageable example, we restrict ourselves to the logical gates NOT, AND, and OR. We also consider circuits with three inputs and one output, and the physical factors aforementioned.

In the sequel we will introduce the problem by first considering the features TOY offers for specifying logical circuits, what are its weaknesses, and how they can effectively be solved with the integration of constraints in TOY(FD) .

Example 1. FLP Simple Circuits. Here we show the FLP approach that can be followed for specifying the problem stated above. We use patterns to provide *intensional* representation of functions. The alias `behavior` is used for representing the type `bool` $\rightarrow$ `bool` $\rightarrow$ `bool` $\rightarrow$ `bool`. Functions of this type are intended to represent simple circuits which receive three Boolean inputs and return a Boolean output. Given the Boolean functions `not`, `and`, and `or` defined elsewhere, we specify three-input, one-output simple circuits as follows.

```
i0, i1, i2 :: behavior           notGate :: behavior -> behavior
i0 I2 I1 I0 = I0                 notGate B I2 I1 I0 = not (B I2 I1 I0)
```

```
i1 I2 I1 I0 = I1
i2 I2 I1 I0 = I2

andGate, orGate :: behavior -> behavior -> behavior
andGate B1 B2 I2 I1 I0 = and (B1 I2 I1 I0) (B2 I2 I1 I0)
orGate B1 B2 I2 I1 I0 = or (B1 I2 I1 I0) (B2 I2 I1 I0)
```

Functions `i0`, `i1`, and `i2` represent inputs to the circuits, that is, the minimal circuit which just copies one of the inputs to the output (in fact, this can be thought as a fixed multiplexer - selector). They are combinatorial modules as depicted in Figure 2. The function `notGate` outputs a Boolean value which is the result of applying the NOT gate to the output of a circuit of three inputs. In turn, functions `andGate` and `orGate` output a Boolean value which is the result of applying the AND and OR gates, respectively, to the outputs of three inputs-circuits (see Figure 2).

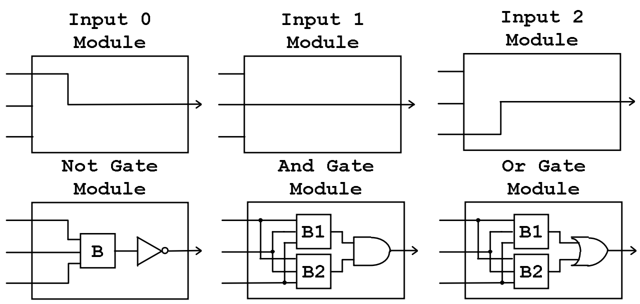

Figure 2: Basic Modules.

These functions can be used in a higher order fashion just to generate or match topologies. In particular, the higher order functions `notGate`, `andGate` and `orGate` take behaviors as parameters and build new behaviors, corresponding to the logical gates NOT, AND and OR. For instance, the multiplexer depicted in Figure 3 can be represented by the following pattern:

```
orGate (andGate i0 (notGate i2)) (andGate i1 i2)
```

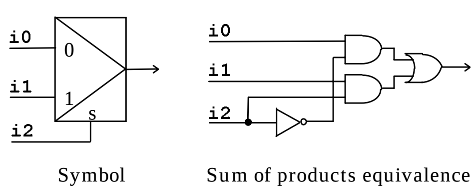

Figure 3: Two-Input Multiplexer Circuit.

This first-class citizen higher order pattern can be used for many purposes. For instance, it can be compared to another pattern or it can be applied to actual values for its inputs in order to compute the circuit output. So, with the previous pattern, the conjunctive goal:

```
P == orGate (andGate i0 (notGate i2)) (andGate i1 i2),
O == P true false true
```

is evaluated to `true` and produces the substitution `O == false`. The rules that define the behavior can be used to generate circuits, which can be restricted to satisfy some conditions. If we use the standard arithmetics, we could define the following set of rules for computing or limiting the power dissipation.

```
power :: behavior -> int
power i0 = 0
power i1 = 0
power i2 = 0
power (notGate C) = notGatePower + (power C)
power (andGate C1 C2) = andGatePower + (power C1) + (power C2)
power (orGate C1 C2) = orGatePower + (power C1) + (power C2)
```

Then, we can submit the following goal (provided the function `maxPower` acts as a problem parameter that returns just the maximum power allowed for the circuit)

```
power B == P, P < maxPower.
```

in which the function `power` is used as a behavior generator[2]:

As outcome, we get the following solutions (computed answers): $\{\langle$`i0`, $\{$`P==0`$\}$, $\{\}$, $\{\}\rangle$, $\langle$`i1`, $\{$`P==0`$\}$, $\{\}$, $\{\}\rangle$, $\langle$`i2`, $\{$`P==0`$\}$, $\{\}$, $\{\}\rangle$, $\langle$`not i0`, $\{$`P==1`$\}, \{\}, \{\}\rangle, \ldots,$ $\langle$`not (not i0)`, $\{$`P==2`$\}$, $\{\}$, $\{\}\rangle, \ldots$ $\}$, where each solution is denoted by a set of 4-tuples $\langle E, \sigma, C, \delta\rangle$, where E is a TOY expression, σ is the set of variable substitutions, C is a set of disequality constraints, and δ is the set of pruned domains. Declaratively, it is fine; but our operational semantics requires a head normal form for the application of the arithmetic operand `+`. This implies we reach no more solutions beyond $\langle$ `not (` ... `(not i0)` ... `)`, `maxPower`, $\{\}$, $\{\}\rangle$ because the application of the fourth rule of `power` yields to an infinite computation. This is solved by recurring to successor arithmetics where `notGatePower`, `andGatePower` and `orGatePower` are of type `nat`, i.e.:

```
data nat = z | s nat                plus :: nat -> nat -> nat
                                    plus z Y = Y
                                    plus (s X) Y = s (plus X Y)

power' :: behavior -> nat           less :: nat -> nat -> bool
power' i0 = z                       less z (s X) = true
power' i1 = z                       less (s X) (s Y) = less X Y
power' i2 = z
power' (notGate C) = plus notGatePower (power' C)
power' (andGate C1 C2) =plus andGatePower (plus (power' C1) (power' C2))
power' (orGate C1 C2) = plus orGatePower (plus (power' C1) (power' C2))
```

[2]Equivalently and more concisely, `power B` $<$ `maxPower` could be submitted, but doing so we make the power unobservable.

So, we can submit the goal `less (power' P) (s (s (s z)))`, where we have written down explicitly the maximum power (3 power units).

With the second approach we get a more awkward representation due to the use of successor arithmetics. The first approach to express this problem is indeed more declarative than the second one, but we get no termination. FD constraints can be profitably applied to the representation of this problem as we show in the next example.

Example 2. CFLP(FD) Simple Circuits. As for any constraint problem, modelling can be started by identifying the FD constraint variables. Recalling the problem specification, circuit limitations refer to area, power dissipation, cost, and delay. Provided we can choose finite units to represent these factors, we choose them as problem variables. A circuit can therefore be represented by the 4-tuple state ⟨area, power, cost, delay⟩. The problem formulation consists of attaching this state to an ongoing circuit so that state variables reflect the current state of the circuit *during* its generation. By contrast with the first example, we do not "generate" and then "test", but we "test" when "generating", so that we can find failure in advance. A domain variable has a domain attached indicating the set of possible assignments to the variable. This domain can be reduced during the computation. Since domain variables are constrained by limiting factors, during the generation of the circuit a domain may become empty. This event prunes the search space avoiding to explore a branch which is known to yield no solution. Let's firstly focus on the area factor. The following function generates a circuit characterized by its state variables.

```
type area, power, cost, delay = int
type state = (area, power, cost, delay)
type circuit = (behavior, state)

genCir :: state -> circuit
genCir (A, P, C, D) = (i0, (A, P, C, D))
genCir (A, P, C, D) = (i1, (A, P, C, D))
genCir (A, P, C, D) = (i2, (A, P, C, D))
genCir (A, P, C, D) = (notGate B, (A, P, C, D)) <==
      domain [A] ((fd_min A) + notGateArea)  (fd_max A),
      genCir (A, P, C, D) == (B, (A, P, C, D))
genCir (A, P, C, D) = (andGate B1 B2, (A, P, C, D)) <==
      domain [A] ((fd_min A) + andGateArea)  (fd_max A),
      genCir (A, P, C, D) == (B1, (A, P, C, D)),
      genCir (A, P, C, D) == (B2, (A, P, C, D))
genCir (A, P, C, D) = (orGate B1 B2, (A, P, C, D)) <==
      domain [A] ((fd_min A) + orGateArea)  (fd_max A),
      genCir (A, P, C, D) == (B1, (A, P, C, D)),
      genCir (A, P, C, D) == (B2, (A, P, C, D))
```

The function `genCir` has an argument to hold the circuit state and returns a circuit characterized by a behavior and a state. (Please note that we can avoid the use of the state tuple as a parameter, since it is included in the result.) The template of this function is like the previous example. The difference lies in that we perform domain pruning during circuit generation with the membership constraint `domain`, so that each time a rule is selected, the domain variable representing area is reduced by the size of the gate selected by the operational mechanism. For instance, the circuit area domain is reduced by a number of `notGateArea` when the rule for `notGate` has been selected. For domain reduction we use the reflection functions `fd_min` and `fd_max`, which respectively return the minimum and maximum values of a variable.

This approach allows us to submit the following goal:

```
domain [A] 0 maxArea, genCir (Area, Power, Cost, Delay) == Circuit
```

which initially sets the possible range of area between 0 and the problem parameter area expressed by the function `maxArea`, and then generates a `Circuit`. Recall that testing is performed during search space exploration, so that termination is ensured because the add operation is monotonic. The mechanism which allows this "test" when "generating" is the set of propagators, which are concurrent processes that are triggered whenever a domain variable is changed (pruned). The state variable delay is more involved since one cannot simply add the delay of each function at each generation step. The delay of a circuit is related to the maximum number of levels an input signal has to traverse until it reaches the output. This is to say that we cannot use a single domain variable for describing the delay. Therefore, considering a module with several inputs, we must compute the delay at its output by computing the maximum delays from its inputs and adding the module delay. So, we use new fresh variables for the inputs of a module being generated and assign the maximum delay to the output delay. This solution is depicted in the following function:

```
genCirDelay :: state -> delay -> circuit
genCirDelay (A, P, C, D) Dout = (i0, (A, P, C, D))
genCirDelay (A, P, C, D) Dout = (i1, (A, P, C, D))
genCirDelay (A, P, C, D) Dout = (i2, (A, P, C, D))
genCirDelay (A, P, C, D) Dout = (notGate B, (A, P, C, D)) <==
  domain [Dout] ((fd_min Dout) + notGateDelay) (fd_max Dout),
  genCirDelay (A, P, C, D) Dout == (B, (A, P, C, D))
genCirDelay (A, P, C, D) Dout = (andGate B1 B2, (A, P, C, D)) <==
  domain [Din1, Din2] ((fd_min Dout) + andGateDelay)(fd_max Dout),
  genCirDelay (A, P, C, D) Din1 == (B1, (A, P, C, D)),
  genCirDelay (A, P, C, D) Din2 == (B2, (A, P, C, D)),
  domain [Dout] (maximum (fd_min Din1) (fd_min Din2)) (fd_max Dout)
genCirDelay (A, P, C, D) Dout = (orGate B1 B2, (A, P, C, D)) <==
  domain [Din1, Din2] ((fd_min Dout) + orGateDelay) (fd_max Dout),
  genCirDelay (A, P, C, D) Din1 == (B1, (A, P, C, D)),
  genCirDelay (A, P, C, D) Din2 == (B2, (A, P, C, D)),
  domain [Dout] (maximum (fd_min Din1) (fd_min Din2)) (fd_max Dout)
```

Observing the rules for the AND and OR gates, we can see two new fresh domain variables for representing the delay in their inputs. These new variables are constrained to have the domain of the delay in the output but pruned with the delay of the corresponding gate. After the circuits connected to the inputs had been generated, the domain of the output delay is pruned with the maximum of the input module delays. Please note that although the maximum is computed *after* the input modules had been generated, the information in the given output delay has been propagated to the input delay domains so that whenever an input delay domain becomes empty, the search branch is no longer searched and another alternative is tried. Putting together the constraints about area, power dissipation, cost, and delay is straightforward, since they are orthogonal factors that can be handled in the same way. In addition to the constraints shown, we can further constrain the circuit generation with other factors such as fan-in, fan-out, and switching function enforcement, to name a few. Then, we could submit the following goal:

```
domain [A] 0 maxArea, domain [P] 0 maxPower, domain [C] 0 maxCost,
domain [D] 0 maxDelay, genCir (A,P,C,D) == (B, S),
switchingFunction B == sw
```

where `switchingFunction` could be defined as the function that returns the result of a behavior `B` for all its input combinations, and `sw` is the function that returns the intended result (`sw` is referred as a problem parameter, as well as `maxArea`, `maxPower`, `maxCost`, and `maxDelay`).

5 Conclusions and further work

We have presented CFLP(FD), a functional logic programming approach to FD constraint solving, which we think may be profitably applied to solve typical problems in the artificial intelligence area. We have shown how FD constraints can be defined as functions and therefore integrated naturally on FLP languages. Due to its functional component, CFLP(FD) provides better tools, when compared to CLP(FD), for a productive declarative programming. Due to the use of constraints, the expressivity and capabilities of our approach are clearly superior to both those of the functional and purely constraint programming approaches.

We have also presented the language TOY(FD) for CFLP(FD). Our proposal can be applied to a wide range of problems which include all CLP(FD) applications and typical uses of functional programming for combinatorial problems.

Moreover, we have shown by example the benefits of integrating FLP and FD. In particular, we have formulated a CFLP(FD) solution for a hardware design problem to show how to apply FD constraints to a functional logic language, which benefits from both worlds, i.e., taking functions, higher order patterns, partial applications, non-determinism, logical variables, and types from FLP and domain variables, constraints, and propagators from the FD constraint programming. This leads to a more declarative way of expressing problems which cannot be reached from each counterpart alone. Note also that our approach is far more declarative than other constraint programming systems as algebraic constraint programming languages (OPL [7], AMPL [3]), mainly since they do not benefit neither from complex terms and patterns nor from non-determinism.

Due to space limitations, we have not presented formally the CFLP(FD) framework in this paper and this is the subject of a further paper (in preparation). For the interested reader we briefly say that for the execution mechanism of the language we have seamlessly integrated constraint solving into a sophisticated, state-of-the-art execution mechanism for lazy narrowing.

Our implementation translates CFLP(FD)-programs into Prolog-programs in a system equipped with an efficient constraint solver [8].

In addition, we claim that our approach can be extended to other kind of interesting constraint systems, such as non-linear real constraints, constraints over sets, or Boolean constraints, to name a few. For this reason, we plan to generalize the CFLP(FD) setting to a generic constraint domain X as done in the CLP setting [9].

References

[1] N. Beldiceanu. *Global Constraints as Graph Properties on a Structured Network of Elementary Constraints of the Same Type*. 6th International Conference on Principles and Practice of Constraint Programming, Springer LNCS 1894, pp:52–66, Singapore, 2000.

[2] M. Carlsson, G. Ottosson and B. Carlson. *An Open-Ended Finite Domain Constraint Solver*. 9th International Symposium on Programming Languages: Implementations, Logics and Programs, Springer LNCS 1292, pp:191–206, Southampton, 1997.

[3] R. Fourer, D. M. Gay and B. W. Kernighan. *AMPL: A Modeling Language for Mathematical Programming*. Scientific Press, 1993.

[4] A. J. Fernández, T. Hortalá-González and F. Sáenz-Pérez. *TOY(FD): User Manual, latest version*, July, 2002. Available at `http://www.lcc.uma.es/∼afdez/cflpfd/`.

[5] M. Hanus. *The Integration of Functions into Logic Programming: A Survey*. The Journal of Logic Programming (Special issue "*Ten Years of Logic Programming*"), 19-20:583–628, 1994.

[6] P. Van Hentenryck. *Constraint Satisfaction in Logic Programming*. The MIT Press, 1989.

[7] P. Van Hentenryck. *The OPL Optimization Programming Language*. The MIT Press. 1999.

[8] T. Hortalá-González and F. Sáenz-Pérez. *Interfacing a Functional Logic Language with a Finite Domain Solver*. 11th International Workshop on Functional and (Constraint) Logic Programming, Grado, Italy, 2002.

[9] J. Jaffar and M. J. Maher. *Constraint Logic Programming: A Survey*. The Journal of Logic Programming, 19/20:503–582, 1994.

[10] F. J. López-Fraguas and J. Sánchez-Hernández. *TOY: A Multiparadigm Declarative System*. 10th International Conference on Rewriting Techniques and Applications, Springer LNCS 1631, pp. 244–247, Trento, 1999. The system and further documentation including programming examples is available at `http://babel.dacya.ucm.es/toy` and `http://titan.sip.ucm.es/toy`.

[11] M. Rodríguez-Artalejo. *Functional and Constraint Logic Programming*. Constraints in Computational Logics, Springer LNCS 2002, pp. 202–270, 2001.

[12] N. F. Zhou, *Channel Routing with Constraint Logic Programming and Delay*. 9th International Conference on Industrial Applications of Artificial Intelligence, pp. 217-231, Gordon and Breach Science Publishers, 1996.