

The Case for Dynamic Flexible Constraint Satisfaction

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Constraint satisfaction has a successful history of practical application. As CSP has been applied to more complex real problems, however, it has become increasingly clear that the classical formulation is insufficient. There are two main areas of weakness: firstly, the inability to deal with *flexibility* in the problem description in case no ‘perfect’ solution exists, and secondly the ability to deal gracefully with changes to the problem structure.

In order to address the first weakness, classical CSP techniques have been extended to incorporate different types of flexible constraints. The flexible constraints used attempt to model the ‘soft’ constraints often found in real problems. The different methods of extending classical CSP to model flexibility are known under the umbrella term of flexible CSP (FCSP) [2, 3].

Similarly, the techniques of *dynamic* constraint satisfaction (DCSP) have been developed to overcome the assumption of a static problem structure. In order to model problems which change uncertainly over time, constraints are added to (*restriction*) and removed from (*relaxation*) the current problem description as necessary (*rr*DCSP, [1]). A related approach, known as *recurrent* DCSP (*rc*DCSP, [6]) is founded on the fact that many alterations to a problem are temporary and that these changes may be subsequently reversed. Specialised approaches re-use the solution to the previous problem in a dynamic sequence to guide the solution of a new problem instance. In order to model problems whose state changes based on the assignments of one or more variables, special constraints are introduced which serve to *activate* sub-parts of the problem structure given certain assignments (*a*DCSP, [5]).

The two types of extension to classical CSP separately offer significant advances in the range of problems that CSP techniques can solve. Little, however, has been done in the area of combining the two disparate extensions to classical CSP to produce dynamic flexible CSP (DFCSP), a framework able to model the changes in a dynamic environment, while retaining the greater expressive power afforded by flexible CSP. DFCSP techniques would support a greater number of real problems than currently possible. In particular, within a dynamic environment where time may be limited, the ability of flexible CSP to produce the best current solution *anytime* will prove invaluable.

Given multiple existing methods of supporting both flexible constraints and dynamic problems, DFCSP is an umbrella term for a range of possible instances that capture different concepts of dynamicity and flexibility (figure 1). The *x* and *y* dimensions denote different instances of dynamic and flexible CSP respec-

		Dynamic CSP Methods				
		<i>rr</i> DCSP	<i>rc</i> DCSP	<i>a</i> DCSP	<i>rr/a</i> DCSP	<i>rc/a</i> DCSP
Flexible CSP Methods	Leximin Fuzzy	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
	Discrimin Fuzzy	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
	Fuzzy	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
	Necessity-Based	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
	Subset Rated +ve	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
	Weighted/Pref +ve	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
	Weighted +ve	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
	MAX	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
		⋮	⋮	⋮	⋮	⋮

DFCS Instance

Fig. 1. The Matrix of Possible Instances of DFCS

tively. A third dimension could be added to this matrix, comprising the solution methods for each associated DFCS instance. One instance, fuzzy *rr*DFCS, has been explored extensively in [4].

Although relatively sparsely populated currently, the x dimension could be extended by combining *a*DCSP and either *rr*DCSP or *rc*DCSP. This would allow problems to be modelled which both change over time *and* exhibit changes in structure based on certain assignments. Suggested names are *a/rr*DCSP and *a/rc*DCSP as shown in the figure. Of course, these can be further combined with flexible CSP techniques to create even more powerful instances of DFCS. Potential applications of DFCS are wide, encompassing many dynamic problems that require more flexibility than classical CSP can provide. Examples include planning, scheduling, machine vision, model-based reasoning, and game-playing.

References

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