

Coping with the wickedness of public policy problems: Approaches for decision-making under deep uncertainty

Kwakkel, JH; Haasnoot, M; Walker, WE

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1 **Coping with the wickedness of public policy problems:**
2 **approaches for decision-making under deep uncertainty**

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4 Jan H. Kwakkel (corresponding author)

5 j.h.kwakkel@tudelft.nl

6 +31 (0)15 27 88487

7 Faculty of Technology, Policy and Management

8 Delft University of Technology

9 Jaffalaan 5

10 2628 BX Delft, the Netherlands

11

12 Warren E. Walker

13 w.e.walker@tudelft.nl

14 Faculty of Technology, Policy and Management

15 Delft University of Technology

16 Jaffalaan 5

17 2628 BX Delft, the Netherlands

18

19 Marjolijn Haasnoot

20 Marjolijn.Haasnoot@deltares.nl

21 Deltares,

22 P.O. Box 177,

23 2600 MH Delft, the Netherlands

24

25 Faculty of Technology, Policy and Management

26 Delft University of Technology

27 Jaffalaan 5

28 2628 BX Delft, the Netherlands

29

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31 In many planning problems, planners face major challenges in coping with
32 uncertain and changing physical conditions, and rapid unpredictable socio-
33 economic development. How should society prepare itself for this confluence of
34 uncertainty? Given the presence of irreducible uncertainties, there is no
35 straightforward answer to this question. Effective decisions must be made under
36 unavoidable uncertainty (Dessai et al. 2009; Lempert et al. 2003). In recent
37 years, this has been labeled as decision-making under deep uncertainty. Deep
38 uncertainty means that the various parties to a decision do not know or cannot
39 agree on the system and its boundaries; the outcomes of interest and their
40 relative importance; the prior probability distribution for uncertain inputs to the
41 system (Lempert et al. 2003; Walker et al. 2013); or decisions are made over
42 time in dynamic interaction with the system and cannot be considered
43 independently (Haasnoot et al. 2013; Hallegatte et al. 2012). From a decision
44 analytic point of view, this implies that there are a large number of plausible
45 alternative models, alternative sets of weights to assign to the different outcomes
46 of interest, different sets of inputs for the uncertain model parameters, and
47 different (sequences of) candidate solutions (Kwakkel et al. 2010).

48

49 Decision-making under deep uncertainty is a particular type of wicked problem
50 (Rittel and Webber 1973). Wicked problems are problems characterized by the
51 involvement of a variety of stakeholders and decision-makers with conflicting
52 values and diverging ideas for solutions (Churchman 1967). What makes wicked
53 problems especially pernicious is that even the problem formulation itself is
54 contested (Rittel and Webber 1973). System analytic approaches presuppose a
55 separation between the problem formulation and the solution. In wicked
56 problem situations this distinction breaks down. Solutions and problem
57 formulation are intertwined with each other. Depending on how a problem is
58 framed, alternative solutions come to the fore; and, vice versa, depending on the
59 available or preferred solutions, the problem can be framed differently. Even if
60 there is agreement on the difference between observed and desired outcomes,
61 rival explanations for the existence of this difference are available, and hence
62 different solutions can be preferred. An additional factor adding to the
63 wickedness is that decision-makers can ill afford to be wrong. The consequences
64 of any decision on wicked problems can be profound, difficult if not impossible
65 to reverse, and result in lock-ins for future decision-making. Planning and
66 decision-making in wicked problem situations should therefore be understood
67 as an argumentative process, where the problem formulation, a shared
68 understanding of system functioning and how this gives rise to the problem, and
69 the set of promising solutions, emerge gradually through debate among the
70 involved decision-makers and stakeholders (Dewulf et al. 2005).

71

72 When even the problem formulation itself is uncertain and contested, planning
73 and decision-making requires an iterative approach that facilitates learning

74 across alternative framings of the problem, and learning about stakeholder
75 preferences and tradeoffs, all in pursuit of a collaborative process of discovering
76 what is possible (Herman et al. 2015). Modeling and optimization can play a role
77 in facilitating this learning. They can help in discovering a set of possible actions
78 that is worth closer inspection, and make the tradeoffs among these actions
79 more transparent (Liebman 1976; Reed and Kasprzyk 2009).

80

81 Under the moniker of 'decision-making under deep uncertainty', a variety of new
82 approaches and tools are being put forward. Emerging approaches include
83 (multi-objective) robust decision-making (Kasprzyk et al. 2013; Lempert et al.
84 2006), info-gap decision theory (Ben Haim 2001), dynamic adaptive policy
85 pathways (Haasnoot et al. 2013), and decision scaling (Brown et al. 2012). A
86 common feature of these approaches is that they are exploratory model-based
87 strategies for designing adaptive and robust plans or policies. Although these
88 frameworks are used in a wide variety of applications, they have been most
89 commonly applied in the water domain, in which climate change and social
90 change are key concerns that affect the long-term viability of current
91 management plans and strategies. Liebman (1976) recognized that water
92 resources planning problems are wicked problems in which modeling,
93 simulation, and optimization cannot be straightforwardly applied. In recent
94 years, this observation has been reiterated (Herman et al. 2015; Lund 2012;
95 Reed and Kasprzyk 2009).

96

97 If decision-making under deep uncertainty is a particular type of wicked
98 problem, to what extent do the recent methodological advances address some of

99 the key aspects of what makes wicked problems wicked? To answer this
100 question, we look at two exemplary approaches for supporting decision-making
101 under deep uncertainty — (multi-objective) robust decision-making and
102 dynamic adaptive policy pathways. We first briefly outline each approach, and
103 then discuss some of the ongoing scientific work aimed at integrating the two
104 approaches. This sets the stage for a critical discussion of these approaches and
105 how they touch on the key concerns of supporting decision-making in wicked
106 problem situations.

107 **Robust Decision-Making**

108 Robust Decision-Making (RDM) (Lempert et al. 2006) emphasizes an iterative
109 approach to planning in which candidate strategies are tested across a very large
110 number of scenarios and, in light of insights gained from this model-based
111 scenario analysis, candidate strategies can be improved. The overarching
112 concern is with the development of a strategy that produces satisficing results in
113 as large a set of scenarios as possible. In RDM, the first step is a generic policy
114 analytic activity that aims at conceptualizing the system under study, the key
115 uncertainties pertaining to the system, the main policy levers, and the outcomes
116 of interest. The second step is case generation, or exploratory modeling (Bankes
117 et al. 2013). In this step, the behavior of one or more models of the system under
118 study is systematically explored across the identified uncertainties, and the
119 performance of candidate strategies is assessed. The third step is scenario
120 discovery (Bryant and Lempert 2010). Using statistical machine learning
121 algorithms, the results of the exploratory modeling are analyzed to reveal the
122 conditions under which strategies perform poorly. These conditions reveal

123 vulnerabilities of the strategies, in light of which they can be modified. The
124 fourth step is tradeoff analysis, in which the performance of the different
125 strategies are compared across the different outcome indicators, thus providing
126 an additional source of information that can be used in redesigning strategies.
127 The steps can be iterated until a satisficing robust strategy emerges.

128

129 Multi-objective Robust Decision-Making (MORDM) (Kasprzyk et al. 2013) is an
130 extension of Robust Decision-Making that adds a multi-objective optimization
131 search for solutions prior to performing the exploratory modeling and scenario
132 discovery. The multi-objective optimization is used to generate a set of
133 promising planning alternatives that illustrate the key tradeoffs on the relevant
134 objectives. Robust Decision-Making is subsequently used to assess the
135 robustness of each of these planning alternatives to a wide range of deeply
136 uncertain futures. Kasprzyk et al. (2013) also discuss various visual analytics
137 techniques that can be used to assess the tradeoffs across multiple objectives
138 and the robustness of the various alternatives. A key point of the visual analytics
139 is that both RDM and MORDM aim at facilitating a discussion among
140 stakeholders and decision-makers, rather than dictating a single optimal solution
141 (Singh et al. 2015).

142

143 RDM has been applied to strategic planning problems in a diverse set of fields,
144 including economic policy (Seong et al. 2005), climate change (Lempert et al.
145 2003; Lempert et al. 1996), flood risk management (Fischbach 2010), sea level
146 rise (Lempert et al. 2012), energy resource development (Popper et al. 2009),
147 and water resources management (Groves 2005; Groves and Lempert 2007;

148 Lempert and Groves 2010; Matrosov et al. 2013; Matrosov et al. 2013). MORDM
149 has been applied to water resources planning management (Herman et al. 2014;
150 Kasprzyk et al. 2013) and ecosystem management (Singh et al. 2015).

151 **Dynamic Adaptive Policy Pathways**

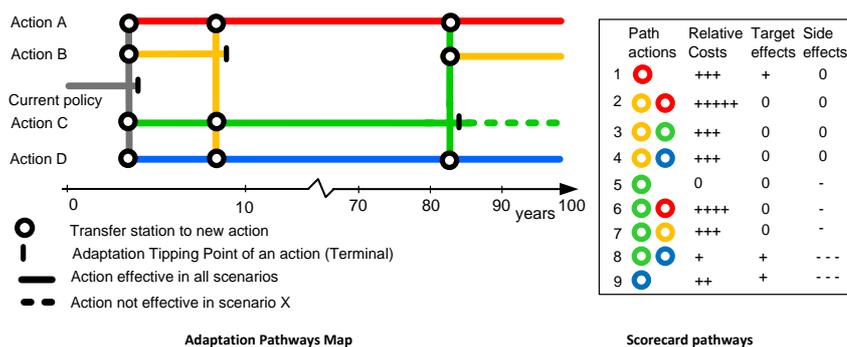
152 The Dynamic Adaptive Policy Pathways (DAPP) (Haasnoot et al. 2013) approach
153 is based on the concept that, in light of deep uncertainties about the future, one
154 needs to design dynamic adaptive plans. Such plans contain a strategic vision of
155 the future, commit to short-term actions, and establish a framework to guide
156 future actions. It is a fusion of adaptive policymaking (Hamarat et al. 2013;
157 Kwakkel et al. 2010; Walker et al. 2001) and adaptation tipping points (Haasnoot
158 et al. 2012; Kwadijk et al. 2010; Offermans 2012).

159

160 The first step in DAPP is to describe the setting, including objectives, constraints,
161 major uncertainties, and a definition of success, and to assess current and future
162 vulnerabilities and opportunities. The specified uncertainties are used to
163 generate an ensemble of plausible futures in the form of (transient) scenarios.
164 Next, the conditions under which the status quo starts to perform unacceptably
165 (adaptation tipping points) are assessed for the relevant uncertainties using
166 expert judgment and/or model simulations. The timing of an adaptation tipping
167 point ('use-by date') is derived from linking the use-by conditions with scenarios,
168 or from the changing performance over time resulting from transient or semi-
169 static model simulations. This reveals if and when policy actions are needed to
170 reach the desired outcomes. Based on this problem analysis, policy actions are
171 identified to address vulnerabilities and seize opportunities, and their conditions

172 and timing of adaptation tipping points is assessed based on their efficacy in
 173 reaching the desired outcomes over changing conditions or time. Once the set of
 174 policy actions is deemed adequate, alternative pathways can be designed and
 175 evaluated. A pathway consists of a concatenation of policy actions, where a new
 176 policy action is activated once its predecessor is no longer able to meet the
 177 definition of success. Based on the evaluation of the pathways, a manageable
 178 number of preferred pathways can be identified. These preferred pathways can
 179 be improved through contingency planning, which requires the specification of
 180 'corrective', 'defensive', and 'capitalizing' actions, and an associated monitoring
 181 system with trigger values that would result in the implementation of the
 182 actions. In light of the final Adaptation Pathways Map, a plan for action can be
 183 made, which specifies the actions to be taken immediately, the developments to
 184 monitor, and when next actions of a pathway should be taken to stay on track of
 185 the preferred pathway.

186



187

188 **Figure 1 An example of an Adaptation Pathways Map and a scorecard presenting the costs and**
 189 **benefits of the 9 alternative pathways presented in the map (adapted from Haasnoot et al. 2013)**

190 Figure 1 shows a stylized example of an Adaptation Pathways Map. In the map,
 191 starting from the current situation, targets begin to be missed after four years.

192 Following the line of the current policy, one can see that, after four years, there

193 are four options. Actions A and D should be able to achieve the targets for the
194 next 100 years in all climate scenarios. If Action B is chosen after the first four
195 years, a tipping point is reached within about five years; a shift to one of the
196 other three actions will then be needed to achieve the targets (follow the lines of
197 action B). If Action C is chosen after the first four years, a shift to Action A, B, or D
198 will be needed in the case of Scenario X (follow the solid line of action C). In all
199 other scenarios, the targets will be achieved for the next 100 years (the dashed
200 line of action C).

201

202 Adaptation pathways can be developed in a variety of ways. Haasnoot et al.
203 (2012) systematically assess adaptation tipping points and explore options after
204 an adaptation tipping point across a range of transient climate scenarios through
205 simulations; Haasnoot et al. (2013) derive the pathways from expert judgment
206 on adaptation tipping points; Haasnoot (2013) derives pathways from expert
207 written storylines and game simulations, and Kwakkel et al. (2014) use a multi-
208 objective robust optimization approach.

209

210 The adaptation pathway approach has been applied to a variety of cases. Most
211 notably, it forms the underpinning of the Dutch Delta Programme (Delta
212 Programme 2014) and it has been used in the Thames Estuary 2100 project
213 (Reeder and Ranger online). Haasnoot et al. (2013) demonstrate the adaptation
214 pathway approach with an example drawn from the Dutch Delta Programme
215 focused on the Lake IJsselmeer area in the Netherlands. Rosenzweig and Solecki
216 (2014) adopt the notion of adaptation pathways to discuss climate adaptation in

217 New York after hurricane Sandy. Other applications are ongoing. For example,
218 the approach is currently being used in Bangladesh and Indonesia.

219 **RDM and DAPP in wicked problem situations**

220 We have presented RDM and DAPP as two distinct approaches to supporting
221 decision-making under deep uncertainty. There are, however, commonalities
222 between the approaches. For example, both DAPP and RDM rely on a
223 participatory scoping of the problem and the use of sets of scenarios to identify
224 vulnerabilities. A vulnerability in the context of RDM is the set of uncertain
225 developments under which a policy fails. This is closely related to the idea of an
226 adaptation tipping point in DAPP. There are also complementarities between the
227 approaches. RDM has a strong emphasis on the iterative process of scenario
228 discovery and policy refinement. RDM is less well developed with respect to the
229 architecture of policies that can be adapted over time. In contrast, DAPP focuses
230 on the adaptive policy architecture, but is more open ended on how to design
231 policies that fit this adaptive architecture. Hence, researchers are increasingly
232 working on combining elements from both approaches (Groves et al. 2014).

233

234 Both RDM and DAPP emerged as planning approaches in the presence of deep
235 uncertainty. Looking at these approaches in light of the characteristics of wicked
236 problems, how well do they hold up?

237

238 Looking at the literature on RDM and MORDM, we observe that there is a strong
239 focus on supporting deliberation through analysis. In an evaluative study of
240 scenario discovery, Parker et al. (2014) found that scenario discovery is able to

241 summarize the information contained in a large ensemble of simulation runs in
242 an easily understandable way. Users appreciated the ability to analyze tradeoffs,
243 and found the results to be quite unambiguous. This ability to analyze tradeoffs
244 is particularly apparent in the multi-objective extension to RDM, where the set of
245 solutions found through optimization is not handled as the final set of possible
246 solutions. Instead it offers a starting point for learning about the problem, about
247 possible solutions, and about tradeoffs (Kasprzyk et al. 2013; Singh et al. 2015).
248 If no clearly preferred solution is found, at least it is learned that the problem
249 framing needs to be adapted. Moreover, the iterative process of policy
250 refinement through modeling supports learning and computer-assisted
251 reasoning (Bankes et al. 2001).

252

253 There are, however, several facets of wicked problems to which RDM does not
254 offer a clear answer. RDM starts from the idea of scoping a problem by defining a
255 system boundary and agreeing on outcomes of interest. Once these are set and
256 models are developed or tuned to fit with this scoping, it will be hard and often
257 expensive, although not impossible, to revise this in light of what is being
258 learned. That is, RDM assumes substantial consensus among decision-makers
259 and stakeholders on the system under study. It is therefore not surprising that
260 RDM practitioners often stress the importance of using existing models that are
261 accepted by the various decision-makers and stakeholders (Lempert et al. 2013).

262 Another issue that is not extensively addressed in the RDM literature at present
263 is the fact that, in many complex wicked problem situations, decisions are largely
264 irreversible, there is no right to be wrong, and there is path dependency. RDM
265 helps in reducing the scenarios under which an action fails with its iterative

266 improvement of the robustness of candidate actions, but does not provide
267 detailed guidance on how to design plans that can be adapted over time, nor
268 does it offer support for analyzing path dependency and lock-ins. It is exactly
269 here that there exist complementarities with the DAPP approach, which focuses
270 more strongly on making the path dependency between actions, and the
271 presence or absence of lock-ins, more transparent.

272

273 Examining DAPP as an approach for supporting decision-making on wicked
274 problems, there are several aspects that stand out. First, DAPP strongly
275 emphasizes the importance of keeping multiple pathway options open to the
276 future, which helps alleviate the irreversibility of decisions and reduces the risk
277 of being wrong. Pathways make lock-ins transparent and help foster
278 understanding of which options are left open given a certain choice now.
279 Moreover, pathways specify future actions that can be taken if the initial actions
280 prove to be insufficient. Second, some of the work on model-based support for
281 the design of adaptation pathways has explicitly approached it as a multi-
282 objective problem (Kwakkel et al. 2014), where support is focused on creating
283 clarity with respect to tradeoffs among competing decision alternatives. Third,
284 DAPP does not dictate a single solution; instead, it helps produce a map of
285 possible routes into the future; and can, for example in combination with the
286 Perspectives method (Offermans 2012; Offermans et al. 2011), present the
287 consequences of different values and perspectives of stakeholders. In light of
288 this, decision-makers and stakeholders can have an informed debate on which
289 actions they would like to take in the future, with an awareness of how these
290 actions might affect their solution space in the future.

291

292 There are several facets of wicked problems to which adaptation pathways are
293 less well suited. Similar to RDM, DAPP assumes that the outcomes and system
294 boundaries are largely uncontested. The process envisioned by DAPP also limits
295 possibilities to change the system conceptualization over the course of the
296 analysis. This is not impossible, but might be costly. Another less well-developed
297 aspect is the computer-assisted learning about a problem that is one of the
298 strengths of RDM. DAPP is substantially more open ended in the methods, tools,
299 and techniques one can employ for supporting adaptation pathway design.

300

301 In conclusion, both RDM and DAPP address somewhat different aspects of what
302 makes wicked problems wicked. RDM facilitates the analysis of tradeoffs and the
303 iterative learning about a policy problem. DAPP helps in studying the
304 reversibility of decisions and offers insight into future actions that can be taken if
305 the initial actions prove to be insufficient. This suggests that research on
306 combining RDM with DAPP is a fruitful direction for future work.

307

308 Both RDM and DAPP still struggle with the fact that, in many wicked problems,
309 the problem definition itself is open to change and co-evolves with solutions that
310 are suggested, and that rival system boundaries and conceptualizations may be
311 present. In the context of model-based support for decision-making, a relatively
312 precise and unambiguous system conceptualization is required, which can be at
313 odds with the wicked nature of the problem under study. The exploratory
314 modeling approach advocated for supporting decision-making under deep
315 uncertainty (McInerney et al. 2012) can be used to at least partly alleviate this

316 concern. Kwakkel et al. (2013), for example apply scenario discovery using two
317 models that represent substantially different conceptualizations of the system
318 under study. Similarly, Auping et al. (2015) explore the consequences of
319 alternative strategies for coping with societal aging using three distinct
320 conceptualizations of how public support for societal aging policies develop.
321 Pruyt and Kwakkel (2014) apply a similar multi-model approach to identify
322 effective policies for reducing homegrown terrorism, where the three models are
323 inspired by rival explanations for the emergence of homegrown terrorists. These
324 examples demonstrate that it is at least technically feasible to handle multiple
325 partially incommensurable system conceptualizations in a single exploratory
326 modeling approach.

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