

1 **Water Resources Systems Analysis: A Bright Past and a**
2 **Challenging but Promising Future**

3 David E. Rosenberg A.M.ASCE¹, Kaveh Madani, A.M.ASCE²

4 Our field of water resources systems analysis is now experiencing one of its most exciting eras
5 where scientists, decision makers, and funding agencies want to apply systems approaches to
6 solve varied, complex, uncertain, and interdisciplinary resource management problems. Solving
7 these problems presents great opportunities for us to engage in complex, real-world decision-
8 making and make positive changes. However, to capitalize on these opportunities, we as a field
9 must also overcome several large challenges related to problem identification, integration, blind
10 use of systems tools, a focus on optimality, and harnessing big data. To overcome, we must look
11 back to find what we have accomplished, why we have sometimes failed, and how we can
12 improve upon our past work.

13 In May 2013, we had the privilege to organize and facilitate a thought-provoking panel
14 discussion at the Environmental Water Resources Institute (EWRI) Congress in Cincinnati, Ohio
15 where different researcher and practitioner panelists spanning multiple generations plus esteemed
16 audience members discussed the past and future of water resources systems analysis. Here, we

¹ Assistant Professor, Department of Civil and Environmental Engineering and Utah Water
Research Laboratory, Utah State University, 4110 Old Main, Logan, UT 84322-4110.
david.rosenberg@usu.edu

² Alex Alexander Assistant Professor, Department of Civil, Environmental and Construction
Engineering, University of Central Florida, 4000 Central Florida Blvd., Orlando, FL 32816.
kaveh.madani@ucf.edu

17 distill some of the key points that emerged during the discussion that we think should guide our
18 systems analysis work and research in the years and decades ahead.

19 **1. There are a wide range of tools and techniques to apply and use**

20 Water resources systems analysts can make use of a wide range of tools and techniques to
21 identify the relevant components of a system and study the interactions among those
22 components. Since the Harvard Water Project and earlier, techniques like linear, non-linear,
23 multi-objective, and dynamic programming as well as evolutionary algorithms, multi-criteria
24 decision making, and game theory have been widely applied to solve complex water problems in
25 practically every region of the world (Harou et al. 2009; Labadie 1997; Madani 2010; Mirchi et
26 al. 2010; Nicklow et al. 2010; Thiessen et al. 1998; Wurbs 2005; Yeh 1985). Although some
27 have criticized these techniques for failing to find actual use by decision makers (Rogers and
28 Fiering 1986), the panelists noted that such assessments were based on a narrow review, only
29 considered academic work, and ignored numerous industry applications like hydropower
30 operations, scheduling, and planning where systems models predominate (Loucks et al. 1984).
31 While early work in the field focused on algorithm development, more recent efforts are tackling
32 the increased complexity of problem formulation and computations using our now larger
33 computing capabilities. Today, we must make our analyses and tools more robust to include
34 multiple objectives and decision makers, integrate more system components, identify larger
35 promising solution sets, and use more readily available data.

36 **2. Develop the science of defining the problem**

37 Our field can benefit greatly from new methods that further develop the science of defining
38 problems—so that expert systems analysts can separately and reproducibly reach comparable

39 problem definitions should they sit down to work on a common problem. Many of our pressing
40 water problems are complex and wicked in that they are multi-faceted, involve competing and
41 often conflicting uses of water, and do not have clear technical or political solutions (Lund
42 2012). They require a systems approach to address. But what does a systems approach mean
43 exactly in this context and what constitutes the system? What are the boundaries that define what
44 we include and exclude from the analysis? These questions are necessarily open in that there is
45 not observable data we can collect and apply to arrive at the single, correct problem definition.
46 Problem definition may also be iterative (Lund 2008) and art as much as science.

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48 Clear problem and system definitions allow others to both understand and reproduce the results
49 that derive from the systems analysis work. Yet the need for a science to reproducibly define
50 problems and systems may foster singular definitions and group-think that overlook important
51 system components or interactions. Thus, we must simultaneously leave open opportunities to
52 learn about the system—make learning endogenous—as we define the problem and subsequently
53 model the system. Learning is often non-linear and may require setbacks for later success.
54 Setbacks may even be integral to ultimate success and they certainly keep things interesting!
55 And in overcoming setbacks, different people will likely learn different things about the system
56 which result in different problem and system definitions that directly oppose the need for an
57 objective, reproducible science of problem definition. Thus, we must balance the competing
58 needs to clearly define our problems and systems, develop the science and methods of
59 reproducible problem definition, and permit—even encourage—opportunities to learn about the
60 problems and systems on which we work. Further, our science of problem definition must be
61 able to accommodate, harmonize, and integrate multiple perspectives.

62 **3. Make integration central**

63 Our practice must include other branches of science such as ecology, biology, sociology,
64 economics, policy, politics, the law, and others. We must consider the steady state as well as
65 spatial and temporal dynamics and path dependencies. In short: we need to integrate all relevant
66 system aspects, states, and metrics. Integration means we must also learn to effectively
67 communicate with those who practice other disciplines: learn and adopt their language(s) as well
68 as adapt our language so they can understand us.

69 We must also think how water interacts with food, energy, environment, politics, and other
70 issues that are quite possibly of larger political importance. In effect, see water as part of a
71 wider—potentially global—system and accordingly expand our boundaries of inquiry. Full
72 integration requires us to think through and model the full set of feedbacks among systems. This
73 more global perspective should guide us to identify strategies to manage water (and other
74 resources) that sustain and enrich our environment for decades and centuries to come. Yet, we
75 must also remember that we have limited capacities to understand and integrate; we can't model
76 everything. This limitation sets up a related and pressing question which is: how much
77 integration and associated complexity is needed and required in our systems models?

78 **4. Start small, work bigger, and don't blindly apply model tools**

79 As we contemplate large-scale integration in our systems models, we need to start small. First,
80 develop simple models that represent key aspects of the system and provide useful insights to
81 solve practical problems. Later, add complexity as needed. And above all else, avoid blindly
82 adopting large, complex tools without properly framing the problem and thinking through the
83 implications of the assumptions embedded into the models and tools we adopt.

84 Our expanding computational capabilities and associated capacity for large-scale integration
85 allow us to confidently solve problems in fractions of seconds that are orders of magnitude larger
86 and more complicated than problems our field's pioneers could ever dream to work on. We
87 readily add model complexities as least publishable units with multiple objectives representing
88 multiple decision criteria, stochasticity, uncertainties, new and faster solution algorithms, etc.
89 Yet, model complexity does not necessarily correlate with usefulness. While highly simplistic
90 models can misguide policy (Madani 2013), super complex models can also be misleading
91 because we end up with black boxes that even the model developers cannot peer inside to
92 understand how or why key model outputs and inputs are connected or correlated.

93 It is much harder to know what complexity is actually required to reach the overarching goals to
94 learn about the problem at hand, solve the problem, and improve decision making. Here, the
95 keep it simple, stupid (KISS) approach can help: reduce complexity only to the level needed to
96 develop an adequate understanding of the water resource system, and advise planners, managers,
97 and decision makers on how to improve their system. Obviously, this level must be achievable
98 with the available personnel, computer, and data resources. All of the above emphasize a parallel
99 need for more work to show the use and impacts of new systems modeling methods by and on
100 decision makers. In the years to come, we must balance the inherent tradeoffs between
101 integration, complexity, available resources, understandability, and adoption as we integrate
102 more features and components into our water resources systems models and draw on an
103 expanding set of systems tools, methods, and models.

104 **5. Move beyond optimal**

105 We must move our systems analysis solution techniques beyond optimal to show decision
106 makers the multiple good (or very good) solutions. For a long time, we have nearly exclusively
107 focused on efficiently finding single optimal and *Pareto*-optimal solutions. And for good reason
108 because optimization allows us to tractably weed out numerous poor-performing solutions in
109 search of the single or Pareto best-performing one(s). Yet modeled optimal is often not optimal
110 from the decision makers' points of view. The modeled and decision makers' objective(s) or
111 constraints may differ. Or there are uncertainties (at the conceptual, formulation, and/or
112 parameter levels) in how the model quantifies the objective(s) and/or constraints. Alternatively,
113 decision makers may not be able to implement or sustain optimal or *Pareto*-optimal solutions
114 prescribed by single- or multi-objective analysis because current models optimize system-wide
115 and group objectives (such as aggregate net benefits) rather than individual objectives for
116 individual stakeholders (Madani and Lund 2011). Two promising techniques that move beyond
117 optimality include (i) near-optimal analysis which identifies all the promising solutions that
118 perform within a specified tolerance of the optimal solution (Brill et al. 1982; Rosenberg 2012)
119 and (ii) threshold detection to identify the range or points where changes in solutions matter
120 (Brown et al. in press). In addition, game theoretic, agent-based, and interactive multi-objective
121 decision making models and tools can further help identify solutions that are reachable, feasible,
122 and stable—near-optimal or *Pareto*-inferior solutions that decision makers may better accept and
123 be more likely implement in practice. Together, these techniques can identify new, promising
124 solutions outside the optimality myopia.

125 **6. Harness big data**

126 We must also make use of recent advances in satellite, sensor, automation, networking, and
127 computation capabilities to harness the ever-increasing avalanche of data and observations about
128 the systems we study and use this data to build more accurate and integrated representations of
129 our study systems. We are downstream users/consumers of data as we rely on hydrologic,
130 demand, infrastructure, system connectivity, downscaled climate, and other data to populate and
131 run our models. Thus, as more data becomes available, we must understand where and how this
132 data originates, choose which data to use, and automate the processes by which we search,
133 discover, access, quality-check, transform, and input big data into our models. We must also get
134 involved in discussions with data collectors and providers of what new data to collect, how to
135 curate it, and provide access. These efforts will speed and ease the tasks of collecting and feeding
136 data to our systems analysis efforts. Simultaneously, the information contained within this data
137 will likely change and transform the structure and content of our models. These capabilities will
138 also soon allow us to push systems model results directly into the hands—literally—of decision
139 makers and users.

140 **7. Wrap up**

141 In the coming years and decades, our water resources systems analysis field holds great promise
142 to help decision makers and researchers solve complex, uncertain, and interdisciplinary resource
143 management problems. To do this, we must draw on a wide range of existing tools, develop the
144 science of defining problems requiring a systems approach to solve, expand the conventional
145 boundaries of water resource problems to include the views and expertise of other disciplines,
146 move beyond identifying optimal and *Pareto*-optimal solutions, and better use available data. We

147 must also start small, work to integrate more aspects of complex systems, and all the while leave
148 ourselves opportunities to learn about the problems and systems we study as well as
149 accommodate and integrate the varied lessons learned and new perspectives we acquire.

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