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Value personas based quantitative decision support: An approach to multi-facetted decision problems

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Resilience management and the planning of critical infrastructure is subject to contested problem framings. Herein, parties to a decision may disagree on the nature of the problem and possible solutions so that finding clear-cut strategies is difficult. Common policy analysis methods, such as cost-benefit analysis, are designed to aid decision making but are limited in the face of multiple contested problem framings. Recent advances propose the use of worldviews to imitate these framings in decision support. This work further refines the approach by replacing the proposed worldviews with a range of 49 unique value personas to represent an extended variety of problem framings with a broader spectrum. Leveraging the human-nature coupled lake model as a use-case to simulate a decision problem, robust decision making (RDM) is employed to evaluate the decision problem resulting from the different framings of the introduced value personas. Compared to using worldviews, the results show that applying societal values to construct value personas benefits the decision support with the ability to evaluate even marginal changes in individual values rather than differing abstract worldviews and enables a more fine-tuneable analysis.

Keywords: societal values, robust decision-making, quantitative decision support, deep uncertainty, multi-actor, worldviews, resilience management.

1. Introduction

Our societies will always be exposed to natural and man-made threats that we cannot foresee nor prepare for to the extent that we could be able to fend them off. Especially for Critical Infrastructures, which are part of the broader system of society and indispensable for its functioning by providing vital goods and services, resilience management is the most promising approach, continuously seeking to improve a system's capacity to handle adverse effects (Bundesministerium für Bevölkerungsschutz und Katastrophenhilfe (BBK) (nd); Carlson et al. (2012); Kanno et al. (2019); Rehak et al. (2019). However, due to the embeddedness of infrastructures in the societal context resilience management entails decision making under deep uncertainty (DMDU), where the decision problems are characterized by contested problem framings Kwakkel and van der Pas (2011). A common DMDU approach is robust decision making (RDM) (Marchau et al. (2019); Lempert et al. (2003)). Lempert and Turner (2020) argue that in practice a society's diversity is significantly misrepresented in typical quantitative decision support due the use of predict-then-act framing approaches, whereby singling out underlying assumptions regarding the future states of the world, decision options and objectives. Using the common lake problem, a human-nature coupled system of a society by a lake, they propose to apply three different worldviews as alternative sets of these assumptions and define rival problem formulations. Their study highlights the importance of tackling DMDU-problems from different perspectives. However, (Lempert and Turner, 2020, p. 846) perceive a worldview as a ”comprehensive conception of the world, comprising a correlated set of values, beliefs, and policy preferences, that shapes how one understands, judges, and acts in the world”, which is an aggregated, high level construct with several drawbacks to be applied to quantitative methods. Schönwandt et al. (2022) show that societal values present a suitable, refined approach to worldviews that enables establishing formal relationships between societal values and quantitative models as well as evaluating the potential impact slight value changes can have on system behavior. They show an improved variability and sensitivity of using societal values compared to worldviews in quantitative decision support. This study expands their approach by introducing value personas to the RDM approach laid out in Lempert and Turner (2020) in order to find robust strategies to the lake model problem.

Derived from Schwartz et al. (2012) and Heblich (2016), 20 different societal values form a value persona, allocated in a circular fashion and sorted by the affinity of neighboring values and the exclusivity of opposite values. Due to the applicability to the lake problem and in order to reduce the complexity for this contribution the set of values to build a value persona is maintained at the four societal values most relevant to the lake problem based on Schwartz et al. (2012):

- Power Resources (POR): A high value of POR resembles a capitalistic trait, the desire to accrue wealth in any form of resource. It does not indicate a form of regulation.
- Stimulation (STI): A high value of STI implies a desire for new input, change, and diversity. This could also imply an affinity for adaptivity, such as in adaptive regulation.
- Conformity Rules (COR): A high value of COR implies a desire for structure, the restraint of actions that could harm others, and the regulation through an authority but does not relate to the kind of regulation as in adaptive or fixed.
- Universalism Nature (UNN): A high value of UNN expresses a desire to protect and care for the well-being of all natural systems based on different reasons. It can also imply human systems and the belief that nature is fragile and needs protection while it is also too complex to manage adequately so that the chain reaction of actions may not always be anticipated correctly.

For this exercise each value can assume one of three states {-1, 0, +1}, which indicates the low, medium, or high importance of one value within its value persona. Importantly, due to the exclusivity rule, within opposite societal value pairs of STI-COR and POR-UNN only one societal value at time can assume a low (-1) or high (+1) state so that if a societal values assume -1 or +1, the opposite value must either be of 0 or +1 and 0 or -1, respectively. In total, this allows a range of 49 value persona combinations to be generated for the analysis. Table 1 shows the first eight value personas (vp) as an example.

Table 1. Example of the first eight of 49 value personas used in this study.

Societal Values	vp00	vp01	vp02	vp03	vp04	vp05	vp06	vp07	...
STI	-1	-1	-1	-1	-1	-1	-1	-1	...
POR	-1	-1	-1	-1	0	0	0	0	...
COR	0	0	1	1	0	0	0	1	...
UNN	0	1	0	1	-1	0	1	-1	...

2. Approach

Following the XLRM framework Lempert et al. (2003), Lempert and Turner (2020) formalized the lake problem so that a worldview determines the parameters for external factors (X), aspects of the system relationships (R), and the objective functions for the outcomes (M) for which robust strategies are sought for the decision variables (L). Thus, a relationship needs to be established between the societal values and the relevant elements of X, R, and M. Applying 49 value personas instead of three worldviews suggests to develop a formalized numerical approach that allows to automatically derive parameters (X), system relationship configurations (R) and objective functions (M) from the input of a value persona.

Schönwandt et al. (2022) present a set of coefficients and constants to convert value personas to lake model parameters (X).

2.1. *Balancing regulation and job training (R)*

Lempert and Turner (2020) argue that the hierarchist and individualist worldviews share an adaptive policy approach, in which the controller takes the recent pollution levels ($\overline{x}[t]$) as well as the warning ($W[t]$) of pollution reaching the threshold into account. Pollution regulation (l_N) under adaptive policy is thus determined by the decision variables (L) b, c, and x^* (target pollution level): $l_N = b * (\overline{x}[t] - x^*) + c * W[t]$. Under fixed regulation l_N is only defined by: $l_N = a$. Job training (l_T) is only related to the decision variable q, which is not dependent on worldviews or value personas.

The logic behind the worldviews implies a specific regulation approach for each worldview that cannot be argued analogously through the value personas. Therefore, the descriptions of societal values from above to deduce the relationship between value personas and regulation preferences. The values of STI and UNN seem relevant factors for the choice between adaptive and fixed regulation. For simplicity, this study assumes that nothing else affects the regulation preferences. Consequently, a high value of UNN and a low value of STI indicates a desire to protect nature while being in favor of consistency and opposing change, which is translated into fixed regulation. In contrast, a high value of STI in combination with a low value of UNN indicates a desire for change and regards nature as manageable, translating into adaptive regulation. A new model parameter μ is introduced to translate the configuration of each value persona into a regulation preference. μ is defined as the sum of products of the STI and UNN positions of a value persona and the coefficients $c_{STI} = -0.25$ for STI and $c_{UNN} = 0.25$ for UNN, additionally complemented by the constant $c_\mu = 0.5$ so that $0 \leq \mu \leq 1$ (Eq. 1).

$$\mu = c_{STI} * STI + c_{UNN} * UNN + c_\mu \quad (1)$$

The desired level of regulation (l_N) is defined in Equation 2. Any value persona configuration that results $\mu = 0$ is defined to indicate adaptive regulation so that b, c, and x^* are enabled, and a is disabled. In contrast, a value persona that results $\mu = 1$ is defined to indicate fixed regulation and only a is enabled while the others are disabled. Any configuration that results $0 < \mu < 1$ is defined as a combined preference and all four decision variables are enabled, weighted by μ.

$$l_N = \mu * a + (1-\mu)(b * (\overline{x}[t] - x^*) + c * W[t]) \quad (2)$$

2.2. *Attributing optimization targets and constraints (M)*

Finally, in order to evaluate the multi-objective decision problem, an objective function needs to be deduced for each value persona. The objective functions in Lempert and Turner (2020) are defined for each worldview and implemented as a set of outcome variables that are chosen from Table 2 as a constraint or maximization/minimization target for the optimization algorithm. For societal values a dedicated definition of objective functions does not exist. Therefore the objective functions need to be deduced for each value persona individually. A three step numeric approach is developed to approximate the objective functions.

Table 2. Description of outcome variables. Measures are evaluated for each simulation run over 100 time steps.

Outcomes	Description
Reliability (R)	Share of positive lake health.
Max Pollution (P)	Largest pollution occurrence.
Total Economy (Y)	Cumulated economic performance.
Employment Traditional (E_T)	Largest employment level in traditional sector.
Unemployment Traditional (U_T)	Largest unemployment level in traditional sector.
Unemployment New (U_N)	Largest unemployment level in new sector.
Employment Inequality (Q_U)	Largest employment inequality between both sectors.
Income Inequality (Q_N)	Largest economic performance gap between both sectors.

First, each societal value−outcome variable relationship is attributed points on a scale of [0,5], where higher points are awarded for stronger relationships. This results in a set of general reference factors that is further called the reference vector (Tab. 3). Second, the societal values are converted into an all-positive numbers point-scale to avoid the equalizing effect of adding negative and positive values during operation. For each societal value {-1,0,1} (as applied in Schönwandt et al. (2022)) is thus substituted with {0,1,2} points respectively. Multiplying the points of each value persona (vp) with the reference factors for the respective outcome variable (RF_m) then establishes a numerical relationship between each value persona and the outcome variables individually ($M_{vp,m}$) (Eq. 3). The points are normalized by the sum of points per value persona in order to obtain the relative importance each outcome variable has for each value persona ($OF_{vp,m}$)(Eq. 4).

Table 3. Reference vector to deduce objective functions for each value persona.

Outcomes	STI	POR	COR	UNN
Reliability (R)	1	2	5	5
Max Pollution (P)	0	2	5	5
Total Economy (Y)	2	5	3	1
Employment Traditional (E_T)	0	2	5	5
Unemployment Traditional (U_T)	1	3	3	2
Unemployment New (U_N)	2	1	3	0
Employment Inequality (Q_U)	1	1	4	2
Income Inequality (Q_N)	0	1	4	2

$$M_{vp,m} = \sum RF_m * vp \tag{3}$$

$$OF_{vp,m} = \frac{M_{vp,m}}{\sum M_{vp}} \tag{4}$$

Third, a filter is applied that determines whether an outcome variable remains informative, is an optimization target, or a constraint for the respective value persona. The filter returns the outcome variable(s) with the highest share as constraints and, from the remaining outcome variables, any with a share greater than 10% as optimization targets. As an exception, the outcome variable Total Economy (Y), as opposed to the others, has no natural limits and can only be an optimization target but not a constraint. The reference vector, the value persona point-scale, and the filter are calibrated by replicating the three worldviews in the form of value personas and using them as reference. Additionally, the results for all 49 value personas are reviewed and some minor adjustments are made to the reference vector in order increase the diversity of outcome variables as optimization targets and constraints. Table 4 illustrates the final distribution of constraints and optimization targets over the collection of value personas. Under the given calibration, multiple value personas have objective functions composed of up to three outcome variables as constraint, combined with at least two and up to seven simultaneous optimization targets.

Table 4. Resulting diversity and distribution of objective functions.

	R	P	Y	E_T	U_T	U_N	Q_U	Q_Y
Constraint	32	11	0	11	0	0	0	0
Optimization	17	34	39	34	39	9	28	12
None	0	4	10	4	10	40	21	37

2.3. *Randomization and evaluation setup*

The analysis setup follows the approaches by Lempert and Turner (2020) as much as possible. The lake model is implemented in Python and the simulation runs are executed with the help of the EMA Workbench library (Kwakkel (2017)). Following the original study (Lempert and Turner (2020), for each value persona the optimization is run for 10'000 iterations over 100 different stochastic realizations for each simulation comprising 100 time steps. The ϵ non-dominated sorting genetic algorithm II (ϵ-$NSGAII$) is applied for optimization (Hadka and Reed (2013); Kollat and Reed (2005)). Preliminary convergence tests over a small selection of value personas applying the $\epsilon-$progress convergence (Hadka and Reed (2013); Kasprzyk et al. (2013)) suggest that a minimum of 20'000 iterations are recommendable and only at around 80’000 iterations all evaluations achieve convergence. Yet, due to physical limitations to handle the computational costs, the evaluation is conducted with the aforementioned limited number of iterations.

3. Results

The results show significant difference to the findings of Lempert and Turner (2020) when comparing a replication of their worldviews by means of value personas as illustrated in Schönwandt et al. (2022). Figure 1 shows the strategies for each persona on the Pareto surface, indicating low economic performance (dark blue) and high economic performance (yellow). The strategies

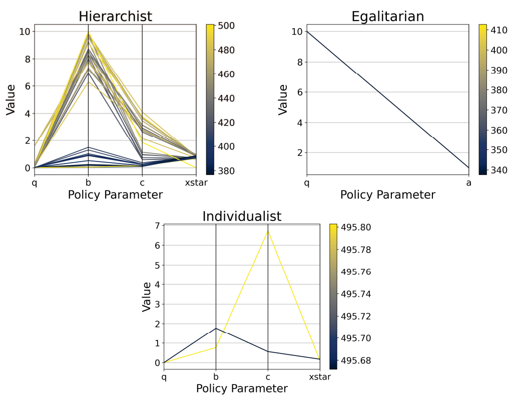

Fig. 1. Results for each replicated worldview, showing the strategies on each Pareto surface.

are presented as line plots in parallel coordinate graphs, indicating the decision variables on the X-axis, the value of each parameter on the Y-axis, and the resulting economic performance as a color value ranging from dark blue (lowest) to yellow (highest). Especially the Egalitarian persona shows only a single strategy on the Pareto front, compared to a range of alternatives in Lempert and Turner (2020). Additionally, the values for variables q, b, and c scale higher, ranging up to 10. Simultaneously, the scale for the total economy ranges only from 380 to 500, whereas Lempert and Turner (2020) indicate performance ranging between 350 and 530. The strategies under the hierarchist persona show some values for b overweighting all values for c, which is the opposite to the findings of Lempert and Turner (2020). Second, the range of 49 value personas shows diverse results. Characteristic examples for the different policy characteristics are represented by the value personas vp03, vp32, and vp42. Table 5 and Table 6 depict the societal value endowments and the respective parameters for the selected value personas. While vp03 has strong concern for conformity (COR) and nature (UNN), vp32 only really values economy (POR) and vp42 values change (STI) and disregards nature (UNN) (Tab. 5).Especially the configurations of the parameters χ^* and Υ^* are important to point out. χ^* defines the critical pollution threshold, which is very low for vp03 and very high for vp32 and vp42. This implies great economic restrictions under vp03 and liberties under vp32 and vp42. At the same time, Υ^* is 0.0 for vp03, which is part of the logistic function for pollution intensity and puts further pressure on the economic’s performance. Figure 2

Table 5. Value personas representation vp03, vp32, and vp42.

Value Persona	STI	POR	COR	UNN
vp03	-1	-1	1	1
vp32	0	1	0	0
vp42	1	0	0	-1

Table 6. Parameters of vp03, vp32 and vp42.

	χ^*	Υ^*	κ	ϵ	τ_1	τ_2	ψ	Δ	γ	μ
vp03	0.2	0.0	10	0.35	0.75	0.85	0.5	0.08	0.1	1.0
vp32	0.7	25	3.5	0.55	0.35	0.45	0.5	0.21	0.25	0.5
vp42	0.9	30	3.0	0.05	0.45	0.55	0.6	0.54	0.20	0.0

presents the resulting strategies and outcomes for vp03, vp32, and vp42. The strategies are presented in the same format as the worldviews above while the outcomes are represented by scatter plots, mapping the economic performance (colored) over the maximum pollution value (Y-axis) and the employment inequality (X-axis). Where vp03 presents one single strategy as the Pareto surface, vp32 and vp42 have multiple strategies that form the Pareto surface. Since the value personas vary between fixed, combined and adaptive policies, the strategies apply different sets of decision variables. vp32 thus combines the fixed and adaptive policy mechanisms both by equal shares ($\mu = 0.5$). While the economic performance of vp32 appears not to be linked to specific values of the decision variables and rather medium levels of maximum pollution and employment inequality, vp42 suggests higher economic performance for higher values of b and c, resulting in lower levels of pollution and employment inequality. The Pareto surfaces of vp32 and vp42 include strategies that hit maximum pollution levels, lining the top of the graphs. Figure 3 illustrates a

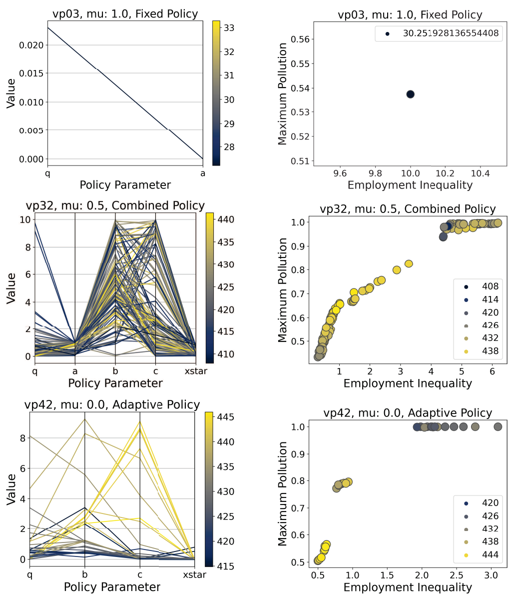

Fig. 2. Illustrating the strategies (left) and their respective outcomes (right) for the value personas vp03, vp32, and vp42 that define the Pareto surface.

collection of best picks from each value persona sorted by maximum pollution and plotted in color in front of the total collection of strategies from all value personas combined (grey crosses). The scatter plot depicts the range of Pareto optimal strategies across the value space. The line graph

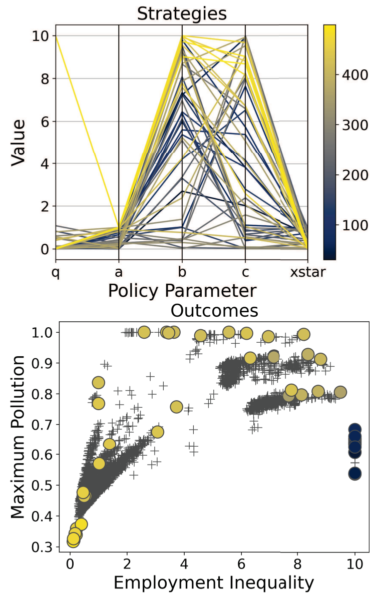

Fig. 3. Best pick strategies (left) by maximum pollution and their outcomes (right) for each value persona, colored by economic performance.

suggest that, although all strategies are best picks from all 49 value personas, those with higher values for b and c tend to perform better economically. Similarly, from the best picks, those strategies resulting in lower maximum pollution and employment inequality are economically also more favorable. The worst economic performance is achieved by strategies with highest employment inequality. The outcome graph also hints at the regret that each value persona bears towards the potential strategies of all other value personas. Even the best pick strategies are located far apart.

4. Discussion

The chosen approach incorporates several important assumptions relating to deducing and implementing the policy preferences and objective functions. However, despite the few points of reference that can be derived from the original study by Lempert and Turner (2020), the range and variability of results supports this approach. Thereby, the formalization of the relationship between societal values and model elements with the help of the reference vector results in a broad variety of outcome variables for the objective functions as optimization targets and constraints alike. Subsequently, the outcomes even show values that exceed the maximum and minimum values achieved with the worldviews approach, which underlines the utility of this approach for applying societal values.

The resulting strategies of the worldviews implementation (Fig. 1) deviate significantly from the findings by Lempert and Turner (2020) even though the same exact parameters are directly input into the model and thus not affected by the assumptions from this research. In contrast, the pick of the random seed is unknown from Lempert and Turner (2020) and an alternative optimization package is used. Nonetheless, comparing the results from using worldviews to using value personas highlights the sizeable information gain provided by using value personas.

The range of strategies and outcomes shows that all value personas with fixed policy approaches ($\mu = 1$) perform very poorly economically and none with adaptive policy approaches ($\mu = 0$) do. This appears to be the case due to the similar dependencies for calculating μ and the values for parameter χ^* (critical pollution threshold). The value personas with fixed policy are simultaneously characterized by $\chi^* <= 0.3$, which sets a very low limit and supposedly stifles the extent to which the lake can benefit the economy. Both μ and χ^* share a relatively large dependency on the societal value UNN, also illustrated by comparing Table 5 and Table 6. In contrast, the other societal values have only little impact to counter this effect, which leads to the aforementioned correlation. While the identified personas perform poorly, it also indicates that the approach allows to produce a broad range of results that reaches beyond the original values used for calibration.

Expanding three worldviews to 49 value personas multiplies the amount of strategies and outcomes to combine and adds a lot more complexity to the evaluation. However, Figure 3 also highlights that there are vastly more possible strategies and outcomes to consider than the worldviews permit to identify. Bringing all alternatives into the scope of evaluation helps to reduce the risks of errors in underlying assumptions and to consider possible changes. The results underline that also neighboring value personas that vary only slightly can result in significantly different strategies and outcomes due to the potentially different attribution of parameters and objective functions. This marginal variability cannot be covered with worldviews. Second, with regard to critical infrastructures this variability is essential to include in the decision analysis in order to account for possible shifts of societal values over time. The results indicate that such shifts could have severe consequences at how an infrastructure system is evaluated. Third, the results further underline that, despite several shortcomings, applying societal values in decision support can be accomplished in mathematically consistent models.

Limiting the number of iterations for the optimization algorithm presents a general drawback for giving decision support. For several value personas the algorithm finds only a very small number of strategies, which could be due to this limitation. Additionally, it is likely that some of the identified strategies are still relatively far away from the actual Pareto surface because the algorithm would have needed more iterations. Nonetheless, the results should be well suited for this proof-of-concept study.

5. Conclusion

Practicing effective resilience management of critical infrastructures is especially challenging due to the embeddedness in society. Over the lifetime of infrastructures the perspectives and needs of a society can change significantly with critical implications for the infrastructure's perceived raison d'être. This study utilizes a reduced set of four out of 20 societal values to generate 49 value personas that are applied to the lake model, a simple and experimental model simulating a human-nature coupled system. Leveraging the range of value personas highlights the sensitivity of parameter choices in complex decision problems and underlines the utility of value personas for identifying the broad spectrum of strategies. Despite the simplicity of the model and various assumptions needed to formalize the relationship between societal values and the lake model, the findings affirm the relevance of this direction of research for resilience management of Critical Infrastructures and quantitative decision support approaches. Due to the limited space, this study is cut short and calls for completion of the RDM analysis to tackle the challenge of finding a robust strategy that applies to all value personas. Future research needs to expand the number of societal values used in value personas, which simultaneously requires to choose a more multi-facetted problem definition so that all societal values are applicable.

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