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IMPROVING PREDICTIONS AND MANAGEMENT OF HYDROLOGICAL EXTREMES

IMPACT ON ADAPTIVE MANAGEMENT OF TRANSPORT SECTOR

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Author(s):	Dmitry V. Kovalevsky (HZG), David Samuel Williams (HZG), María Máñez Costa (HZG)
Contact for queries	Dmitry V. Kovalevsky (dmitrii.kovalevskii@hzg.de)
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Abstract	Inland Waterway Transport (IWT) is a mode of transportation highly vulnerable to hydrological extremes, notably to low flow events in shallow river systems. Low flows occasionally create serious disruptions of IWT operations in present-day climate conditions, and might create more frequent and severe disruptions under projected future climate. Innovative probabilistic water level forecasts developed within EU H2020 IMPREX project, shown to be useful already at present climate and hydrological conditions, are likely to become even more important for decision making under future climate. By substantially reducing the uncertainty of the complex human-technology-environment system under study, these probabilistic forecasts are anticipated to become an important component of strategies designed for adapting IWT and related sectors and stakeholders to hydrological extremes. The remaining components of multi-level uncertainty can be explored with integrated modelling, including system dynamics (SD) models developed within the Interdisciplinary Knowledge Integration approach (IKI-IMPREX)

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List of abbreviations

ABM	agent-based model
ARA	the Amsterdam-Rotterdam-Antwerp set of ports
BVAR	Bayesian vector autoregressive model
DAP	Dynamic Adaptive Planning
DIIM	dynamic inoperability input-output model
GDP	gross domestic product
HTE	human-technology-environment system
IIM	inoperability input-output model
IKI	Interdisciplinary Knowledge Integration
I-O model	input-output model
IWT	inland waterway transport
LUTI	land use - transport interaction models
OD	origin-destination matrix
SD	system dynamics
VAR	vector autoregressive model

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1 Introduction

Inland Waterway Transport (IWT) is a mode of transportation highly vulnerable to hydrological extremes, notably to low flow events in shallow rivers. The operation efficiency of IWT closely correlates to the available water depth along the waterways (Klein and Meißner, 2017; Meißner and Klein, 2015). Innovative probabilistic water level forecasts developed within EU H2020 IMPREX project (Klein and Meißner, 2017), already demanded under present climate and hydrological conditions, are likely to become even more important for decision making under projected future climate, when low-flow events limiting the operations of IWT might become more frequent and severe (Hänsel et al., 2019; Kovalevsky et al., 2018b, 2019).

Therefore, probabilistic water level forecasts supporting navigation operations are anticipated to become an important element of adaptive management processes designed for adapting IWT, and sectors and stakeholders dependent on IWT, to hydrological extremes under current and projected climate. One of the cornerstones of adaptive management is acknowledging the uncertainty and limited predictability of the dynamics of the managed system, and also elaborating efficient practices of managing systems under deep uncertainty. Tools like probabilistic navigation-supporting forecasts are efficient for both understanding and managing the uncertainty related to IWT operations, and affecting the decision-making within IWT itself and the dependent sectors, which will undoubtedly serve as vital technical solutions embedded in adaptive management schemes.

While the uncertainty directly related to water levels and bottlenecks can be analyzed and reduced with probabilistic water-level forecasts, other facets of uncertainty, notably those related to the socioeconomic part of the managed complex human-technology-environment (HTE) system under discussion, still should be taken into account in adaptive decision-making and planning. This calls for development of integrated interdisciplinary modelling tools accounting for multi-level uncertainties of managed systems, tailored for their subsequent use in adaptive management schemes. In the present report, we apply for this purpose the Interdisciplinary Knowledge Integration approach (IKI-IMPREX) developed within EU H2020 IMPREX project (Mánez Costa et al., 2017; Máñez Costa and Kovalevsky, 2018), with qualitative and quantitative system dynamics (SD) modelling as a key tool for 'what-if' simulations and policy analysis of HTE systems under uncertainty.

The report is organized as follows. In Section 2, we discuss the basic concepts of adaptive management. Then we investigate the system dynamic (SD) modelling methodology that is tailored to adaptive management processes related to IWT operations under low flows jointly with probabilistic water level forecasts to substantially reduce the uncertainty of the modelled system. Section 3 provides a literature review of IWT-related SD modelling, while Section 4 describes qualitative and quantitative SD modelling for IWT operations performed within the IKI-IMPREX approach. Section 5 summarizes the implications of SD modelling for adaptive management for IWT-related sectors supported by probabilistic water-level forecasts.

2 Adaptive management: concept and applications to Inland Waterway Transport

Inland Waterway Transport can be regarded as a complex human-technology-environment (HTE) system that experiences the impacts of climate, environmental and socio-economic change.

Over time, a number of paradigms of managing HTE systems affected by climate and environmental change have evolved. Historically, the first, and still dominating, paradigm is the 'command-and-control' approach. Later a concept of integrated management has emerged (notably, with applications to water resource management), and currently a paradigm of adaptive management is evolving (Pahl-Wostl et al., 2007).

Adaptive management is tailored for complex systems where decisions have to be made under conditions of deep uncertainty. Adaptive management accounts for these multi-level uncertainties, and can be viewed as a process of improving the management process and decision rules by learning from successes and failures of management practices in the past. Additionally, exploring adaptation pathways, monitoring environmental and societal drivers, and detecting adaptation strategy tipping points are the elements of adaptive management process. 'Adaptive management is learning to manage by managing to learn' (Bormann et al., 1993). Unlike, for instance, the conventional 'command-and-control' approach, that explicitly or implicitly assumes the high predictability of the managed system, adaptive management acknowledges the limited ability to predict the behaviour of complex systems and the impacts of decisions, emphasises the role of learning, and makes use of self-organizing properties of managed systems. In such a way, a rethink of the role of management under conditions of deep uncertainty takes place (Pahl-Wostl et al., 2007).

To take into account multi-level uncertainties of the managed system, the adaptive management process represents an iterative cycle of several steps visualized in Figure 1. These steps should be participatory with the inclusion of stakeholders (Máñez Costa et al., 2014), to ensure the capability to learn from previous experiences of decision-making.

As a recent development of the adaptive management approach, Dynamic Adaptive Planning (DAP) is highly relevant (Walker et al., 2019). DAP is a method for decision-making under deep uncertainty by designing an adaptable plan that can be corrected as conditions change and new knowledge is gained.

System dynamics (SD) modelling allows to describe the dynamics of complex uncertain interdependent HTE systems. Qualitative SD models deliver insights in systems structure and interdependencies between their elements, while quantitative SD models can support hypothesis testing about plausible futures of managed systems and likely effects of specific managerial decisions on their operation by 'what-if' simulations. In such a way, SD modelling becomes a valuable tool for the adaptive management and DAP that can efficiently support iterative cycles of an adaptive management process by qualitative insights and quantitative simulations.

The present report is primarily devoted to SD modelling related to IWT and impacts of low flows on its operations as a part of adaptive management for IWT that can be used both in the short-term (responding to low flows in current climate conditions) and in the long-term (adapting to low flow in future climate conditions, where the frequency and severity of low flow events can increase substantially). In the next section, we provide a review of relevant previous work on SD modelling of IWT operations.

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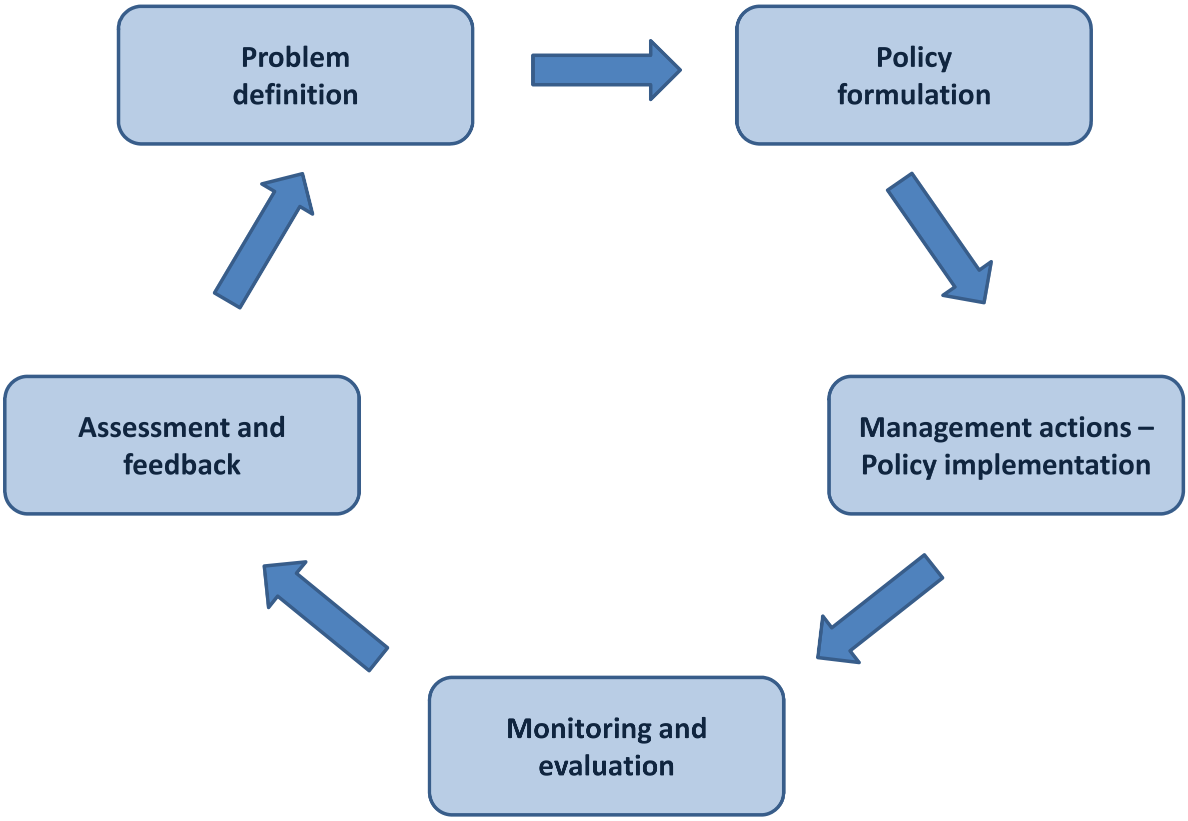

Figure 1: Iterative cycle of policy development and implementation in adaptive management (re-drawn from (Pahl-Wostl et al., 2007))

3 Review of system dynamic modelling of Inland Waterway Transport

3.1 System dynamics in transportation models

Transport-economy models have a long and prominent track record of development and successful application to policy analysis and solving real-world problems related to the transportation sector, including IWT (Beuthe et al., 2014a, 2014b; de Jong et al., 2002; Long et al., 2014; Putman, 1983; Wan and Li, 2018; Zhang et al., 2017). Models differ in breadth of scope and depth of detail, and they are based on different modelling approaches. Some of them explore a multi-method simulation approach (Oztanriseven, 2016) when different components of an integrated model are developed independently, using different modelling methods (e.g. a SD model for one component and an ABM (agent-based model) for another component), and subsequently linked by appropriate methods of model integration (Belete et al., 2017a, 2017b).

SD models (Forrester, 1971; Sterman, 2000) are extensively used in describing the dynamics of socio-natural systems and environmental decision making, including participatory-based techniques of SD modelling co-development (Vennix, 1996; Videira et al., 2017; Voinov and Gaddis, 2017). SD modelling is frequently used for development of components of multi-method simulation approaches, and sometimes a major fraction of the chain of transportation models is built using SD modelling (Fiorello et al., 2010; Long et al., 2014). However, as revealed e.g. by (Stroombergen et al., 2017), the transport/freight/traffic modules themselves are rarely developed using a SD methodology. More often, LUTI-type approaches[1] are chosen for the transport/traffic component of the integrated model, while SD is applied to generate e.g. macroeconomic scenarios affecting other components of the model. An exception is the work by (Stroombergen et al., 2017) describing the traffic with SD, while regional and sectoral economic variables are described with a non-SD approach (with BVAR - Bayesian vector autoregressive models).

Also (Benaich, 2015) consistently models road traffic with SD by adopting cell transmission modelling, where a section of road is divided into several discrete cells, with each cell described as a stock through which transport flow (i.e., the flow of vehicles) passes.[2] This model design allows the simulation of localized congestion events with very small spatial and temporal scales.

The advantages of SD to model transportation compared to more conventional approaches have been outlined in an early program paper by (Abbas and Bell, 1994), with a particular emphasis on applications to strategic policy analysis and SD-based decision support tools. Groothedde (2000) provides a classification of transportation/logistic models distinguishing: (i) static models, that provide ‘a snapshot’ of a process, but do not explore temporal changes in the system; (ii) comparative static models that are able to generate a series of snapshots, yet the dynamical/transitional process itself is not modelled; (iii) [system] dynamic models that simulate continuous changes in systems, including feedback-driven changes, and transitional pathways.

Transport-economy systems are substantially nonlinear dynamical systems, with complex feedbacks between their different components. This opens the prospects for describing them with SD models and tools. The transport-economy systems to be modelled, including the case study of River Rhine IWT considered here, include a number of different actors and stakeholders, that should be properly described in the modelling scheme (Shepherd, 2014). This suggests that such systems can be conveniently described with actor-based system dynamics approaches – an extension of conventional SD modelling with the emphasis on describing socioeconomic systems driven by interactions of several influential aggregate actors, and on control strategies of these actors described by system dynamic tools (Hasselmann and Kovalevsky, 2013; Hasselmann et al., 2015).

In their review (de Jong et al., 2002) illustrate that more freight transport models exist for large-scale applications (international and national models) than for the small-scale (regional, sub-regional and urban models). The current generation of small-scale models often incorporate the description of socioeconomic processes insufficiently. The SD models presented here partially close this gap, as they are focussed on regional scale.

[1] LUTI – land use - transport interaction models

[2] Benaih’s model is applied to the case study of the Brussels ring-road system, that is represented in the model by 164 cells.

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Most transport models are designed within using a four-stage modelling scheme, designed for a particular complex, zonally disaggregated, transport network (Putman, 1983; Stroombergen et al., 2017): (i) trip generation (based on information on/projections of imports from and export to each zone); (ii) trip distribution (calculation of the origin-destination (O-D) matrix that defines the traffic flows connecting the zones); (iii) trip model split (determining the mode of transport); (iv) trip assignment (determining the transport routes). In this conceptual scheme, as applied to the SD models described in the present report, the topology of a network is deliberately simplified in the model design (substantially reducing to a waterway and an alternative route of transport between origin, bottleneck and destination). However, certain concepts from the four-stage sequential scheme outlined above are also used in the proposed SD set-up.

3.2 Modelling disruptive IWT events

A severe low flow situation in a waterway system can become a disruptive event making IWT operations difficult or even impossible.

Socioeconomic SD models are well suited to model disequilibrium dynamics, e.g. the effects of supply-demand imbalances (Kovalevsky and Hasselmann, 2014; Volchenkov, 2016). This makes SD models particularly relevant for assessing the resilience of the systems and exploration of various adaptation options (including climate adaptation). Indeed, it has been argued in previous research (Kortschak and Perrels, 2013) that accounting for disequilibrium effects is important for describing the recovery pathways and adjustments after extreme events. SD models can be applied to modelling disruptive IWT events caused by various reasons (including natural disasters, man-made accidents, potential terrorist attacks etc.).

Below we briefly review recent work on application of SD models and multi-method simulation models to assessment of disruptive IWT events.

(MacKenzie et al., 2012) develop a model of a disruptive IWT event (a sudden inland waterway port closure) with a multi-method simulation approach. The decision-making of individual companies (on whether to reroute commodities via alternative transportation mode, e.g. truck or rail, or to wait until the port re-opens) is simulated by stochastic agent-based simulation based on Bayesian learning of agents. The interdependent impacts of port closure on regional economy are simulated with the inoperability input-output model (IIM) and its dynamic extension, DIIM (dynamic inoperability input-output model). Both approaches are grounded in Leontief's I-O model (input-output model) broadly used in theoretical and applied economics (Leontief, 1936). Leontief's I-O model provides a self-consistent description of interdependent commodity flows among various production sectors in a national or regional economy, but is essentially static in its nature. IIM is a risk-based extension of the I-O model, that allows describing a shift to the new economic equilibrium caused by partial inoperability of certain economic sectors (in the IWT application under discussion – caused by transportation disruption). However, IIM also computes the new equilibrium in a static manner, and therefore the dynamics of the disrupted economy, the transitional effects and recovery pathways are not included in the modelling scheme. DIIM, which can be viewed as an SD approach to describing economic inoperability, allows for explicit dynamic description of transitional effects and subsequent recovery (Lian and Haimes, 2006). Thus, the DIIM methodology is applied in the present study (Section 4.4.2.3; see also Annex B).

The response of IWT operations to disruption events was also studied by SD modelling in (Oztanriseven, 2016). Their SD simulations assess the economic impacts of the accuracy of (uncertain) disruption duration estimation and pay close attention to potentially adverse economic impacts of alternative modes of transfer.

In the next section we present our IKI-IMPREX approach of building integrated interdisciplinary SD models, and apply it to IWT modelling for IWT at River Rhine.

4 SD modelling for transportation on Rhine by IWT supported by probabilistic forecasts

4.1 Brief summary of IKI-IMPREX

The Interdisciplinary Knowledge Integration approach (IKI) has already been described in detail in IMPREX D13.1 'Generic integrative modeling approach guideline' (Mánez Costa et al., 2017), and later additionally in (Máñez Costa and Kovalevsky, 2018). IKI was applied to the Júcar River Basin. Before applying IKI to River Rhine case study in the present deliverable, we first provide a summary of IKI essentials, based on (Máñez Costa and Kovalevsky, 2018).

IKI is a generic integrative modelling approach, applicable to versatile socio-natural systems and case study areas. IKI is developed to incorporate multidisciplinary knowledge on essential drivers of a decision context. Policy-relevant modelling tools are essential for many environmental applications, notably including climate services provision (van den Hurk et al., 2016). In particular, IKI can be efficiently applied to the assessment and to modelling the implementation of adaptation measures in regions exposed to extreme hydrological events.

Central to the IKI process is SD modelling.

The IKI approach can be highlighted with the following sequential scheme:

(i) problem identification and structuring using individual model building exercises with stakeholders;

(ii) problem analysis using group model building exercises;

(iii) a family of integrated models (with different complexity levels) to provide results that can be used at the local level for decision-making; and

(iv) simulations showing efficiency tendencies supporting the optimization of the decision process.

The flowchart of IKI implementation is provided in Figure 2. The IKI process goes through co-production of individual qualitative SD models by stakeholder interviews, to a synthesis of a qualitative SD group-model, to its quantification and application to policy analysis.

IKI allows the inclusion of various complex system perspectives in the modelling framework, to benefit from complementarity of relevant disciplinary knowledge and of understanding of system dynamics by individual stakeholders. Transdisciplinary knowledge is included in the modelling framework through the participation and co-operation of stakeholders and researchers in the model creation process. The core idea of the approach is building a quantitative modelling structure for a given decision context (e.g., water resources management; adaptation to hydrological extremes) allowing the analysis of multiple decision-drivers and their interactions.

Within the IKI approach, a generic model family is developed, where individual model members

- are tailored to different processes and answer different research questions;
- can be based on different modelling methodologies and paradigms; and
- are applicable to different spatial and temporal scales.

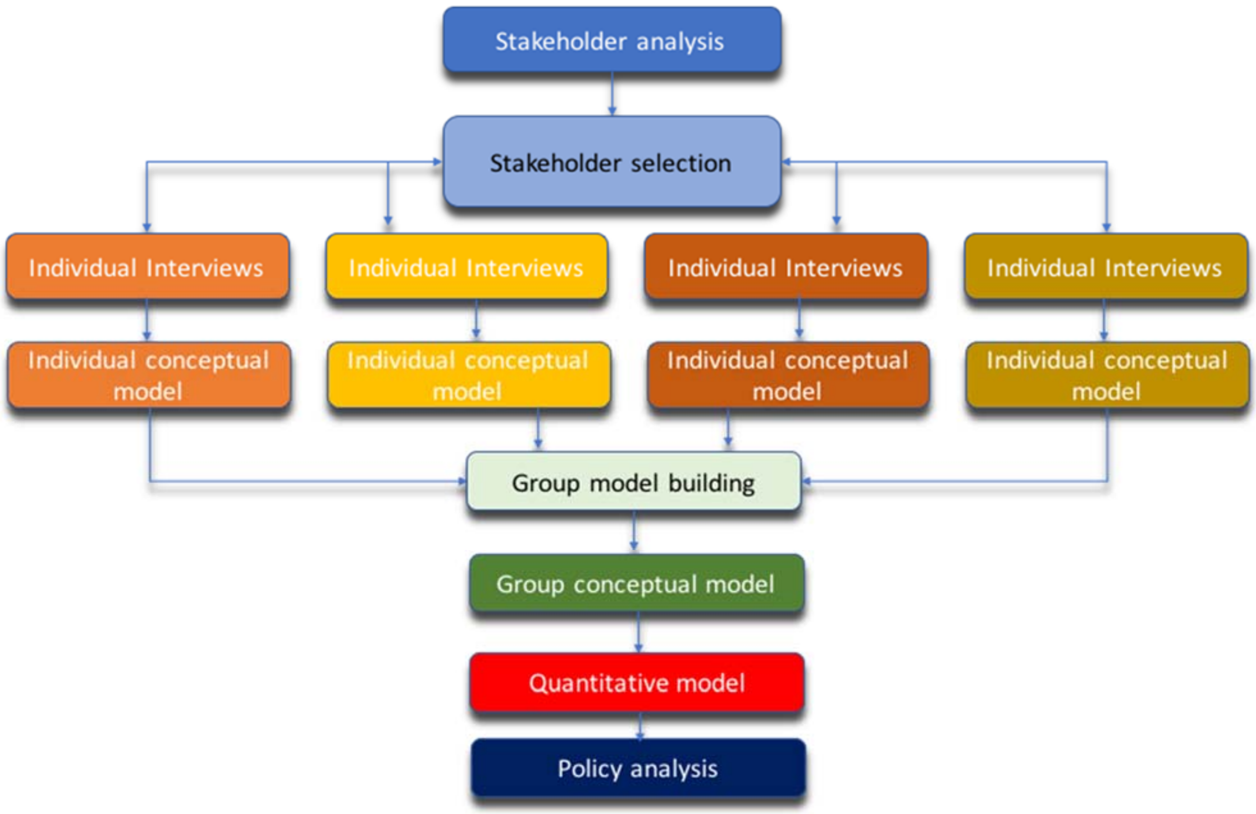

Figure 2: The flowchart of IKI implementation (Máñez Costa and Kovalevsky, 2018)

4.2 SD model design for River Rhine case study

A family of quantitative SD models is developed to describe the process of cargo transportation by IWT under conditions of uncertainty (notably, water-level uncertainty under low flows). To support the adaptive management process development, the model family takes the form of a set of prototype multi-actor models of decision making under conditions of low-flow events and their consequences.

One of the goals of SD modelling is to assess the added value of probabilistic water-level forecasts for the sustainability of supply chains under present and projected climates, including the scenario building scenarios of future IWT operations under projected drier climate with more frequent and severe low flow events.

In general, models might be built either on assumptions of certainty in the dynamics of modelled systems, or account for risk (with probability of outcomes well specified) or uncertainty (where probability of outcomes involves ambiguity). For complex HTE systems and processes, the assumption of certainty is not realistic (see Section 2 above). Thanks to innovative probabilistic water-level forecasts (Klein and Meißner, 2017; Meißner and Klein, 2015), the analysis of the system under study is shifted from an uncertainty domain to a risk domain, as probabilities of foreseen outcomes are now quantified by probabilistic forecasts. However, in other parts of the coupled HTE system, notably in socioeconomic aspects, uncertainties still remain and should be taken into account in the SD modelling scheme. Stochastic SD modelling is a possible approach, and examples are provided below in Section 4.4.2.

4.3 Qualitative SD modelling

4.3.1 Stakeholders involved

Following the IKI approach (Figure 2), modelling for the River Rhine case study started with co-production of individual qualitative SD models by interviews with the following stakeholders:

BASF

The Badische Anlin und Soda Fabrik (BASF) are the world's leading chemical producer and company. They have various business segments, particularly in chemicals and plastics, as well as oil and gas. Their largest German plant is located in Ludwigshafen to which they need to transport large quantities of chemicals for their production processes. They also own power plants which depend on the supply of cargo along the Rhine.

BLN

Koninklijke BLN-Schuttevaer is a Dutch organization of barge-owners and cargo shippers based in Zwijndrecht. They represent over 2500 members at 15 regional departments. As the income of barge-owners and cargo shippers is highly dependent on transportation conditions along the Rhine, they have an interest in the long-term development of water levels

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EnBW

Energie Baden-Württemberg AG is one of the largest energy supply companies in Germany and Europe. They use the Rhine for transporting coal to supply their power plants. Their headquarters are based in Karlsruhe.

Imperial

Imperial Shipping Services GmbH acts as a shipping service with a large fleet of barges and cargo ships, and also chartered vessels. They operate on the Rhine, as well as the Elbe, Main, Danube, and Neckar. They transport dry bulk goods and heavy lift cargo. The loading capacity of their barges and ships heavily depend on water levels in the Rhine. Their headquarters are based in Duisburg.

TransnetBW

Transnet Baden-Württemberg GmbH is responsible for facilitating the supply of energy throughout the region, Germany, and Europe, by operating the electricity transmission grid in Baden Württemberg. They control and monitor the energy flowing through the grid, to ensure grid stability and undertake necessary network planning and development activities. The Rhine is important for their daily operations as the transport of coal for supplying power plants is essential for keeping the energy transmission grid stable. Their headquarters are in Stuttgart.

Figure 3: Location of stakeholders – participants of SD model development – along the River Rhine

4.3.2 Individual SD models

Semi-structured interviews have been carried out with stakeholders presented in the previous section. Based on these interviews, individual qualitative SD models reflecting stakeholder vision of the socio-natural system under study have been developed. While these individual SD models are not provided in public access in the present report because of confidentiality considerations, we present the qualitative SD group model synthesised from these individual models.

4.3.3 Group model

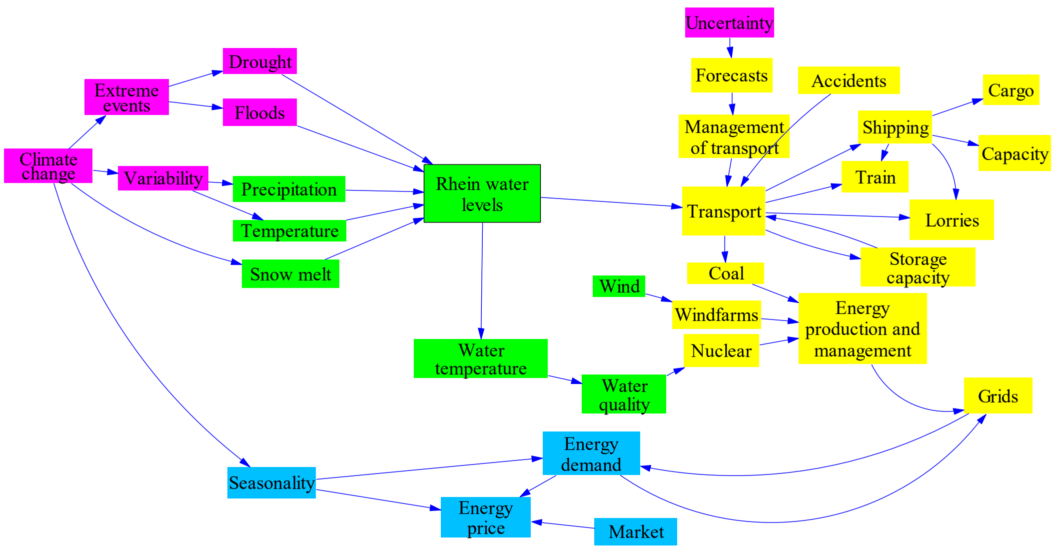

Figure 4: Synthesized Group Model. Color scheme: blue – socio-economic variables; green – natural capital; yellow – activities; pink – risks and impacts

The Group model represents a synthesis of the most important variables and relationships listed in the individual models and allows for a cross-sectoral view on the issues affecting inland waterway transport on the Rhine. Extreme events and variability are both influenced by climate change, leading to short- and long-term droughts and floods, and are also altering precipitation and temperature patterns in the Rhine Basin. This affects water levels and can lead to transport restrictions for cargo ships. Currently, transport managers are making use of forecasts including a forecast uncertainty mapping, to better predict the appropriate loading of ships at the Amsterdam-Rotterdam-Antwerp (ARA) set of ports, and to determine which ships with which

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loading capacity will be needed. When water levels in the Rhine are low, the mode of transport is more variable, with higher utilisation of on-land transportation using road- and rail networks, as well as a higher demand of ships as their loading capacity is reduced, incurring higher costs for the cargo owners.

Transport capacity influences the distribution of coal to power plants to the southern regions of Germany for energy production and management. The demand for coal is determined by the amount of available energy from wind farms and nuclear energy, and on the seasonally variable energy demand. Combined with the energy market, these factors determine the overall energy price.

The synthesised group model is further detailed and quantified, as presented in Section 4.4 below.

4.4 Quantitative SD modelling

4.4.1 Stakeholder types in SD modelling

The SD model family presented below includes models for the IWT and other economic sectors.

Based on the outcomes of the 1st IMPREX Stakeholder Workshop held at BfG, Koblenz, in 2016, the SD modelling is focussed on the following actor/stakeholder types (Klein and Meißner, IMPREX Deliverable D9.1, 2017): (i) skippers; (ii) logistic managers; (iii) transport operators; (iv) harbour/ waterway managers; (v) transmission grid operators; (vi) economists.

The following framework is adopted to describe the decision-making of actors, for instance, the decision of skippers on optimal loading of vessels (Oztanriseven, 2016):

1. Describing the system (SD model), including:
    - Sources of risk and uncertainty
    - Decision alternatives
    - Decision tree
2. Analysis of alternatives
3. Optimal decision strategies (actor-specific)

As an example, the individual skipper, facing the risk of low flow events, has to make a number of decisions, including answering the following questions:

- How much load to take on board of their vessel at the start of the journey?
- What is the optimal start time of the journey in view of an anticipated low flow event?
- If water level at the bottleneck is too low for the loaded vessel to pass, should the skipper wait or, alternatively, (partially) unload the vessel and use an alternative mode of transportation (rail, truck)?

Different actors are facing different alternatives, they adopt different strategies and criteria for their decision-making, which makes the dynamics of a multi-actor model complex and decentralized.

4.4.2 Members of SD model family and simulation results

4.4.2.1 A model of decision-making on optimal loading

As discussed in detail in (Klein and Meißner, 2017a, 2017b), traditionally the short-term water level forecasts are consulted frequently by individual skippers to support their decision-making on optimal loading of vessels under anticipated low flow conditions at bottlenecks. The demand for the forecasts grows during low flow events, as ultimately skippers are responsible for potential economic losses resultant from non-optimal decisions.

Klein and Meißner (2017a, 2017b, 2019a, 2019b) apply the detailed transport cost model for assessing the potential economic benefits of tailored probabilistic forecasts and report the estimates of cost savings for scenarios when probabilistic forecasts are adopted in operational decision-making.

The model considered can be regarded as an optimization model for individual vessel loadings, achieved by minimizing transportation costs borne by individual skippers.

In a multi-actor system, different actors are pursuing different goals and hence optimize different goal functions.

The SD model supplements the model by Klein and Meißner (2017a, 2017b, 2019) by describing a similar yet non-identical optimization problem, with a focus on maximizing the sustainability of IWT-dependent supply chains that are affected by low flow events. The description of the model is provided in Annex A. The optimization procedure maximizes average cargo flows to ensure the sustainability of supply chains, as opposed to minimization of costs borne by an individual skipper, which is the focus of the modelling reported in (Klein and Meißner, 2019a). Among the stakeholder types indicated in Section 4.4.1 above, this optimization setup might be closer to the goals of transport operators and economists.

SD modelling results suggest that, with the goal function changed as compared with the skipper decision making model reported in (Klein and Meißner, 2019a), - from minimization of transportation costs borne by individual skippers to maximization of sustainability of supply chains by maximizing average cargo flows, - the probabilistic forecasts are more efficient than the deterministic forecasts in the new framework as well. More detail on this can be found in Annex A, where the structure of the models and decision strategies of actors are described. Although optimization decisions made by model actors based solely on average water level (i.e., on deterministic forecasts) are quite good, the decisions based on average water level and, additionally, on its forecasted variability (i.e. on probabilistic forecasts) outperform them and prove to be more efficient.

4.4.2.2 Out-of-equilibrium SD modelling of welfare losses caused by low-flow events

In economic theory, welfare loss is defined as the lost welfare as a result of an imbalanced (too much or too little) production and consumption of a good or resource, where the imbalance might be caused, for example, by an externality affecting the production side of the economic system.

Jonkeren et al. (2007) calculate the annual welfare loss caused by low flow events on the River Rhine, based on the analysis of the detailed trip reports database Vaart!Vrachtindicator, which contains data about trips made by IWT in Western Europe. The database includes information

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reported via internet by individual enterprises for individual trips, including the price per ton, date and place of vessel loading and unloading, capacity of the vessel, number of tons transported, type of cargo etc.[3] Data on vessels passing the Kaub bottleneck are taken into account in their analysis. Theoretically, the welfare analysis performed is based on assumptions of perfectly competitive IWT market and perfectly elastic supply of IWT services. When the water level drops in the course of a low flow event, the loads of IWT vessels have to be reduced, and IWT enterprises have to charge higher prices per ton of transported cargo; hence, the economic surplus is reduced. Jonkeren et al. (2007) derive the annual average welfare loss of 28 Mio. EUR for the period 1986-2004, with an outstanding welfare loss of 91 Mio. EUR in 2003 caused by a very dry summer.

Welfare loss estimates reported in (Jonkeren et al., 2007) are based on a comprehensive analysis of a large database; however, the theoretical approach to welfare loss estimate can be defined as essentially static (that means, based on a conventional static analysis of supply-demand curves). At the same time, the IWT disruption triggered by low-flow events and subsequent rise of prices per ton is a substantially out-of-equilibrium economic process. We argue that an out-of-equilibrium SD modelling of the dynamics of supply-demand imbalance and subsequent price adjustment is based on more plausible assumptions than conventional static approach and, therefore, would provide a better description of economic impacts of IWT disruptive event.

With an SD model we extend the approach by (Jonkeren et al., 2007) in two directions. Firstly, we disaggregate the welfare losses into daily values, computed on the daily values of observed or forecasted water levels at the bottleneck. Secondly, we augment the modelling framework by an out-of-equilibrium approximation of price formation dynamics, following earlier modelling work (Hasselmann and Kovalevsky, 2013; Kovalevsky and Hasselmann, 2014), as opposed to instantaneous price adjustment in conventional market clearing approximation. The first extension (disaggregation to daily values) allows the description of the transition process with substantially finer time resolution, while the second extension (out-of-equilibrium price dynamics), as argued above, provides a better justified description of price formation processes adequate for the adopted finer time scales.

Figures 5 and 6 visualize the price per ton of cargo and the daily welfare loss under changing water level. Blue lines on the figures correspond to SD simulations with the conventional equilibrium price model (instantaneous price adjustment, market clearing). Red lines correspond to the extended out-of-equilibrium price adjustment model with a finite price adjustment rate. As seen from the figures, different approximations of price formation dynamics lead to visibly different simulated scenarios of economic dynamics.

With the assistance of probabilistic forecasts in decision-making, the price per ton would rise to a lesser extent from its equilibrium value, and the dynamical pattern of welfare loss would show a less pronounced fluctuation. Simulations for mitigating the IWT disruptions with decisions based on probabilistic forecasts are provided in Section 4.4.2.3 below for a different modelling framework.

[3] More information on Vaart!Vrachtindicator database can be found at www.vaart.nl.

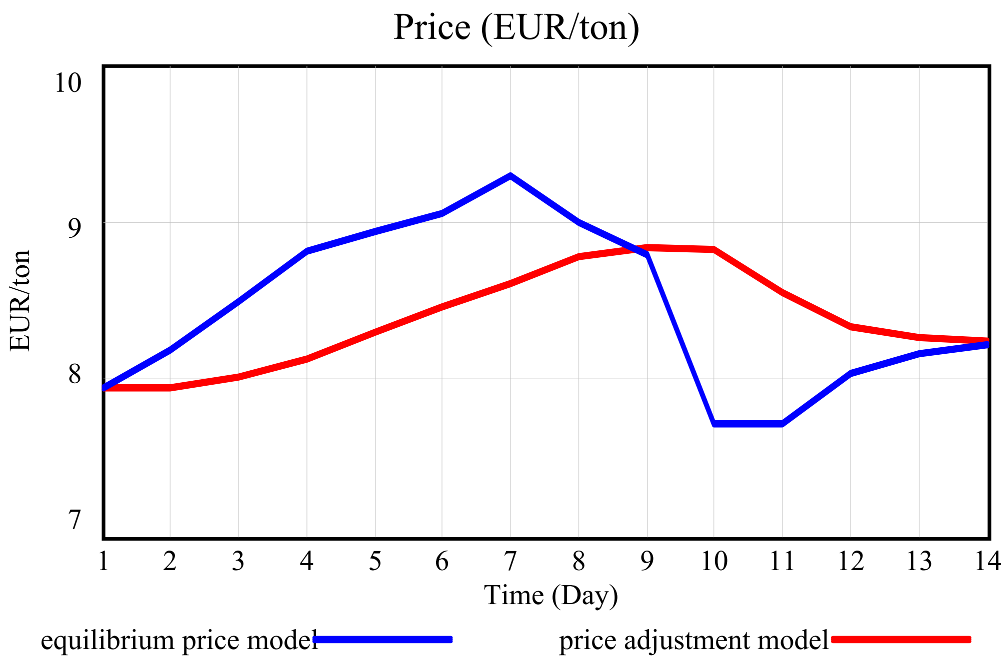

Figure 5: SD simulation of price per ton of cargo changing as a result of a low flow event. Blue line: equilibrium price model (instantaneous price adjustment). Red line: price adjustment model (finite price adjustment rate)

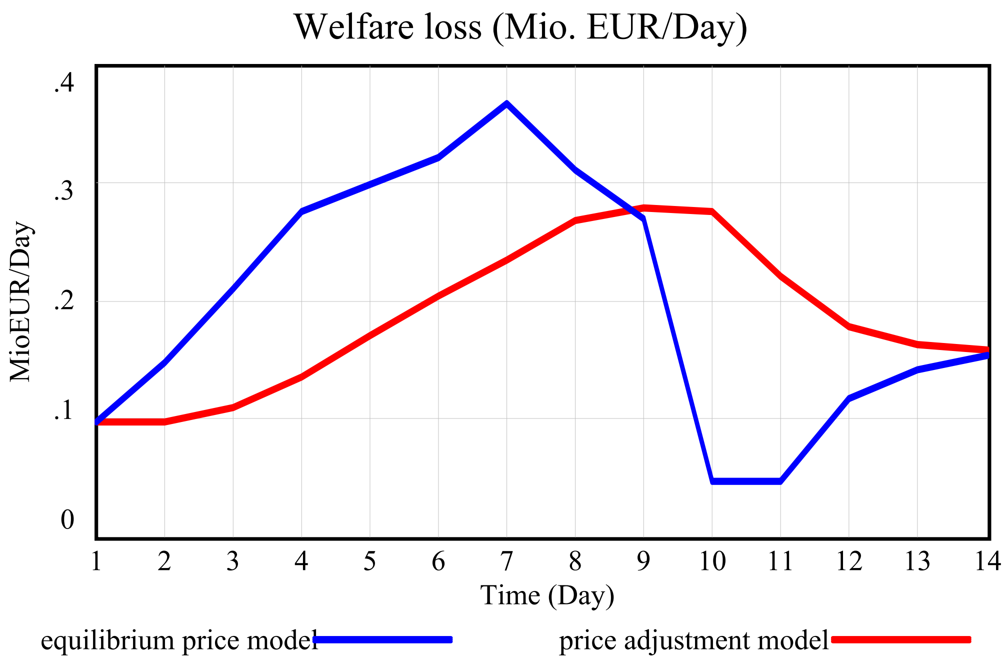

Figure 6: SD simulation of welfare losses in result of a low flow event. Blue line: equilibrium price model (instantaneous price adjustment). Red line: price adjustment model (finite price adjustment rate)

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4.4.2.3 SD extension of DIIM modelling of sectoral impacts of low flow

The DIIM model developed in (Lian and Haimes, 2006) and briefly outlined in Section 3.2 describes regional interdependent infrastructure systems under conditions of temporary reduced operability caused by disruptive events. DIIM describes the transitional economic dynamics after the disruption and the recovery of a regional economy to its equilibrium state. The research interests of the authors of DIIM focus on potential terrorist attacks as disruptive events, but they also acknowledge that disruptions caused by natural disasters can be described within the same modelling scheme as well.

The dynamic framework of DIIM includes: the conventional Leontief technical coefficient matrix **A** which elements a_{ij} indicates the ratio of output from economic sector i used as input to the production of economic sector j (generally, this matrix is available from national I-O accounts); a vector of final sectoral demands; sectoral resilience coefficients defining adjustment rates of individual sectors after the disruption; and a stochastic term accounting for uncertainties of recovery pathways. It should be mentioned that at large simulation times DIIM converges to the static solution of the conventional Leontief I-O model, so the added value of DIIM is in simulating the transitional recovery processes. More detail on DIIM is provided in Annex B.

In Figure 8 DIIM simulations of a recovery of a regional economy after a severe low flow event are presented, both for the 'baseline' scenario of a severe IWT disruption and for the scenario where the disruption is mitigated with the help of probabilistic forecasts. Economic sectors are aggregated to the following three sectors: 1) IWT, 2) IWT-independent sector, 3) IWT-dependent sector. By 'dependence'/'independence' of a sector on IWT strong/weak coupling to IWT iterations parameterized by big/small values of related technology matrix elements a_{ij} should be understood. In particular, the individual stakeholders described in Section 4.3.1 would be included in IWT-dependent sectors. In line with original DIIM methodology, a multiplicative vector stochastic noise is included in the otherwise deterministic scheme (the same realization of the random noise is used for the 'baseline' and the 'probabilistic forecast' simulations).

The initial conditions of sectoral outputs (just before the disruption caused by the low flow event) coincide with the equilibrium state of the economy, as found from the static Leontief I-O model and shown for references in Figure 7. It is assumed that low flow events directly affect the IWT sector, substantially reducing its operations in the 'baseline' scenario (blue line in Figure 8) and reducing them to a lesser extent when operations are supported by probabilistic forecasts (grey line in Figure 8). Due to the interdependency of modelled economic sectors, the IWT-dependent sector also experiences a drop in production with a subsequent gradual recovery. The drop is more pronounced in the 'baseline' scenario than in the 'probabilistic forecast' scenario. Another sector, labelled as 'IWT-independent' experiences a small alteration in production as well. This alteration, in magnitude, is far less pronounced than the production drop experienced by the IWT-dependent sector; however, the difference between the 'baseline' and the 'probabilistic forecast' scenario is still visible in the graph.

The welfare loss model described in Section 4.4.2.2 is focused on monetary variables (price dynamics and the welfare loss by providers and users of IWT services caused by a temporary raise of prices as result of a low-flow event). On the contrary, the DIIM model presented here is more focused on sectoral production, and, commonly to input-output modelling in general, short-term price fluctuations are not included in the modelling scheme. Therefore, these two models can be seen as complementary approaches to modelling a complex transitional process.

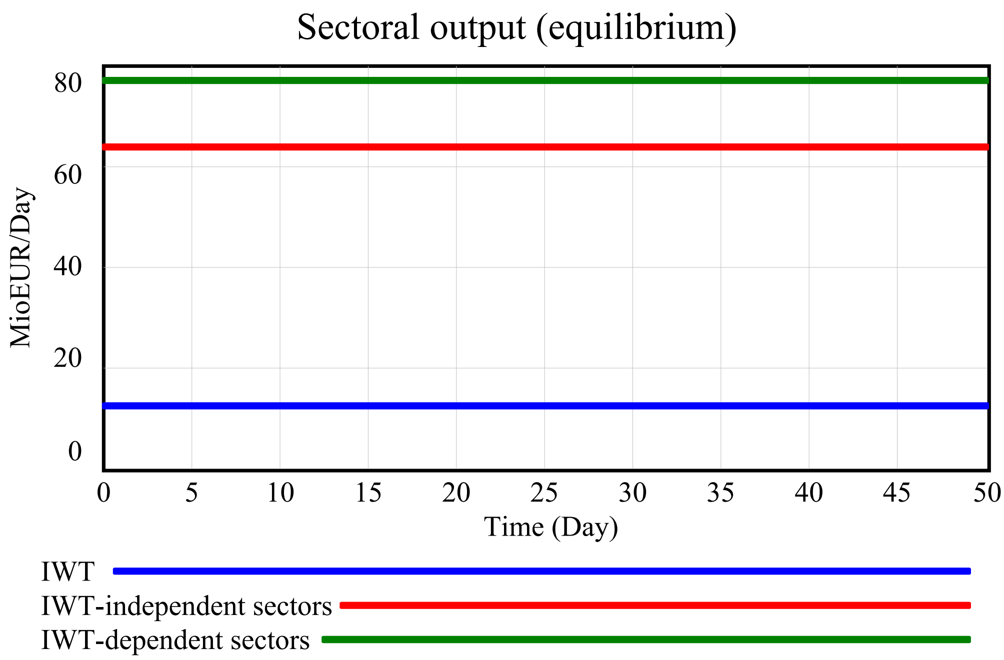

Figure 7: DIIM simulation of a regional economy in its equilibrium state (static case, sectoral outputs do not change in time)

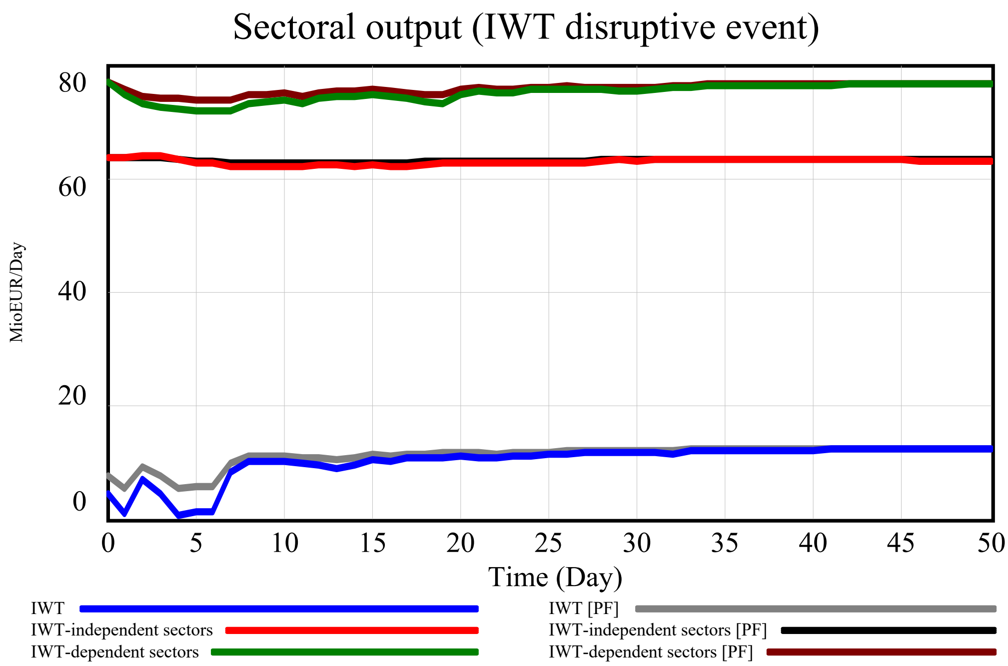

Figure 8: DIIM simulations of sectoral outputs after a disruption caused by a low flow event. Blue, red, green line: case of a severe IWT disruption. Grey, black, brown line: case when the disruption is mitigated with the help of probabilistic forecasts ('[PF]' in the legend)

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5 Impacts of probabilistic water-level forecasts on adaptive management of transport sector: SD model evidence

Tailored probabilistic water-level forecasts allow accounting for uncertainties related to IWT operations under low flows, and also reducing the hydrology-related component of the multi-level uncertainty of the HTE system under study. To a large extent, these forecasts, when incorporated in the decision-making schemes, transform the problem of IWT operations under low flows from uncertainty domain to risk assessment and management domains, as the probabilities of possible outcomes are now quantified by probabilistic forecasts.

While individual skippers have traditionally been the broadest target user group of water-level forecasts, probabilistic forecasts are also in demand by users facing the necessity of decision-making over longer time scales than deterministic forecasts can usually deliver. With a substantial extension of lead time in probabilistic forecast products these stakeholders are getting better support for their longer-term decisions.

As understanding of and coping with uncertainty is a key element of adaptive management procedures (Pahl-Wostl et al., 2007), probabilistic water-level forecasts are anticipated to become a crucial technical element of adaptive management schemes. However, as the uncertainty of the HTE system under study cannot be reduced solely to hydrology-related uncertainty, other dimensions of uncertainty should be explored in these schemes with other complementary tools (see examples of stochastic SD simulations in Section 4.4.2 above). A promising modelling methodology for this is integrated SD modelling (including stochastic SD modelling) that might incorporate probabilistic water-level forecasts as one of the elements of the modelling scheme. Different members of the SD model family might address the demands of stakeholder decision-making at different time horizons, from individual skipper support on optimal loading of their vessels, to assessing the economic impacts of and recovery pathways after disruptions of IWT operation caused by low flows.

One particular application of adaptive management schemes based on probabilistic forecasts and incorporating SD modelling is coal transportation on River Rhine (Kovalevsky et al., 2018b, 2019). Electricity generation in Southern Germany currently heavily depends on coal (unlike in Northern Germany where it predominantly depends on wind farms). IWT is an important mode of transportation of coal on River Rhine, where low flow events make operations of IWT difficult and may lead, in particular, to problems with timely delivery of coal, therefore creating delays and supply constraints for electricity generation (up to potential blackouts). Advanced navigation-related forecasts might increase the sustainability of IWT operations and therefore more efficient operations of supply chains dependent on IWT operation, including transportation of coal and other cargos.

Probabilistic water-level forecasts are likely to become increasingly important for decision-making of stakeholders related to / dependent on IWT operations under conditions of projected climate change that might differ substantially from the hydrological situation and IWT operations in the case study area.

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The work described in the report was partially presented at the following conferences: the 9th International Congress on Environmental Modelling and Software (iEMSs 2018), 24-28 June 2018, Fort Collins, USA (Kovalevsky et al., 2018b); European Climate Change Adaptation Conference 2019, 28-31 May 2019, Lisbon, Portugal (Kovalevsky et al., 2019). The authors are grateful to the participants of these conferences for useful feedbacks.

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Annex A. A model of optimal vessel loading

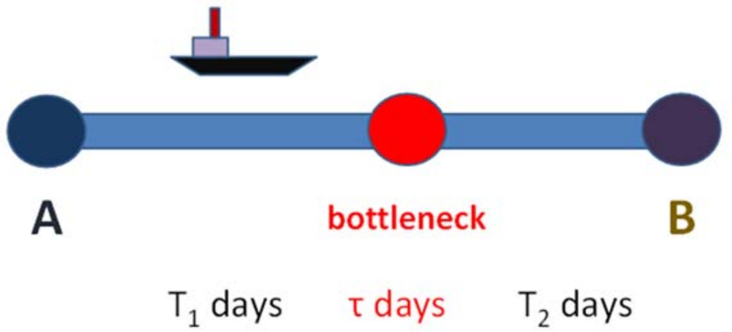

Figure 9: Modelling the optimal loading of the vessel to travel along the waterway with a bottleneck

A model of optimal vessel loading to travel along the waterway with a bottleneck describes the following schematic situation.

Every day a vessel starts its way through the inland waterway at point A (departure), aiming to carry load to point B (destination). On the way, there is a bottleneck, where a vessel can experience problems (and hence be delayed) if its load is too heavy for the water level when reaching the bottleneck.

Travel from point A to the bottleneck takes T_1 days.

Travel from the bottleneck to the point B takes T_2 days.

(Potential) delay at the bottleneck is τ days long.

We assume that, on average, the water level at the bottleneck is known and is equal to d_0. (delivered by 'deterministic forecast', the latter is assumed to predict the correct average water level, but with no information on its probability distribution). The actual water level would, however, be $d_0+\varphi$, where φ is a random variable with zero mean and a certain variance. We assume that its cumulative distribution function (CDF) is known (delivered by probabilistic forecast) and is equal to $F(\varphi)$. [By definition, CDF $F(x)$ is a probability of random variable X to be less than a certain value x.]

The skipper has to make a decision on how much load to take on board at point A.

We assume that the load of the vessel $L(d)$ in case of anticipated water level d at the bottleneck can be chosen at point A according to the algorithm:

$$L(d) = \begin{cases} a\cdot(d-d_{min}) & \text{if } d > d_{min}, \\ 0 & \text{if } d < d_{min} \end{cases} \qquad \text{(A.1)}$$

(if the water level is lower than d_{min} than voyages with cargo are no longer possible).

Or, in other words, if $d = d_0+f$

$$L(f) = \begin{cases} a\cdot(d_0-d_{min}+f) & \text{if } f > d_{min}-d_0, \\ 0 & \text{if } f < d_{min}-d_0 \end{cases} \quad \text{(A.2)}$$

We now introduce the *cargo flow* W, where

W = (load of the vessel)/(time of the voyage) (A.3)

To maximize the cargo flow will be the goal of our optimization problem.

If the actual water level at the bottleneck is lower than that anticipated by the skipper, on which the loading decision was based (the probability of such an outcome is F(f)), then the vessel is delayed at the bottleneck, and

$$W = L(f)/(T1+T2+\tau) \quad \text{(A.4)}$$

Otherwise, there is no delay (the probability of such an outcome is 1-F(f)), and

$$W = L(f)/(T1+T2) \quad \text{(A.5)}$$

In Eqs. (4)-(5), L(f) is given by Eq. (A.2).

On average, with multiple travels and the same loading strategy, the expected value of cargo flow is

$$\langle W\rangle = F(f)\cdot L(f)/(T1+T2+\tau) + (1-F(f))\cdot L(f)/ (T1+T2) \quad \text{(A.6)}$$

If the CDF function F(f) is known (‘delivered by probabilistic forecast’), then the optimal on average loading level f (or $d = d_0+f$) can be derived from the maximization of Eq. (A.6).

Computational examples show that, if the CDF F(f) is known, a better strategy for maximizing average cargo flows can be derived from the optimization outlined above than, for example, if the loading is based on the average water level ($d = d_0$, or $f = 0$ – a solution supported by the deterministic forecast).

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Annex B. The dynamic inoperability input-output model (DIIM)

A brief technical description of DIIM provided in this section is based on the original paper by (Lian and Haimes, 2006).

As a basis of modelling, the Leontief's static input-output (I-O) model is taken. In matrix notation, the model takes the form

$$\mathbf{x}=\mathbf{A}x+\mathbf{c} \tag{B.1}$$

where x_i, the *i*-th component of the vector **x**, represents the output of sector i; the Leontief technical coefficient a_{ij}, an element of the matrix **A**, indicates the ratio of input from sector i to sector j; c_i, the i-th component of the vector **c**, represents the final demand of the i-th sector (i.e. the portion of sectoral output for final consumption by end-users).

The deterministic dynamical generalization of Eq. (B.1) takes the form

$$d\mathbf{x}/dt=\mathbf{K}[\mathbf{A}\mathbf{x}+\mathbf{c}-\mathbf{x}] \tag{B.2}$$

where **K** is the diagonal industry resilience coefficient matrix. The dynamic equation (B.2) is able to describe the transitional process after a disruption in production of one or several sectors; it should be noted, however, that after the end of the transitional (recovery) process, the solution of Eq. (B.2) ultimately converges to the equilibrium solution of the static model (B.1). In the stochastic version of DIIM, a multiplicative noise is added to the r.h.s. of Eq. (B1.2).

To simulate the consequences of the disruption and the recovery to equilibrium, one should integrate the deterministic dynamical equation (B.2), or its stochastic extension, for the initial condition $\mathbf{x}_0$ for vector **x** that deviates from the equilibrium solution of the static model (B.1). By setting the values of one or more components of the vector $\mathbf{x}_0$ at lower values than the corresponding components of the equilibrium solution, a disruption in one or more sectors at the initial time is described. The subsequent dynamical simulation provides the out-of-equilibrium descriptions of recovery to the equilibrium state of the economy.

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