

FIELD GUIDE TO INTERPRETING ENGINEERING TEAM DESIGN BEHAVIOUR WITH SENSOR DATA

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Problem Statement

To reveal the mechanisms inside teams working on complex systems problems, a sociotechnical physics

Inspired ethnography, great thinkers and insightful writers are relevant guides, yet we cannot be sure without uncovering the underlying phenomena with reproducible experiments. Indeed, insightful case studies might be only shadows of the underlying phenomena.

This work is an early attempt to seek the underlying science of teamwork for complexity, and the first principles of sociotechnical systems.

Related Research Insights

1. **Frame problems by well-articulated systems models, increased interactive visualization for real-time exploration, and new sensors for data capture.**
2. **Detect how team attention and activities map to the problem, solution, and social spaces**
3. **Overcome difficulty to reproduce and scale to industrial teams of teams.**

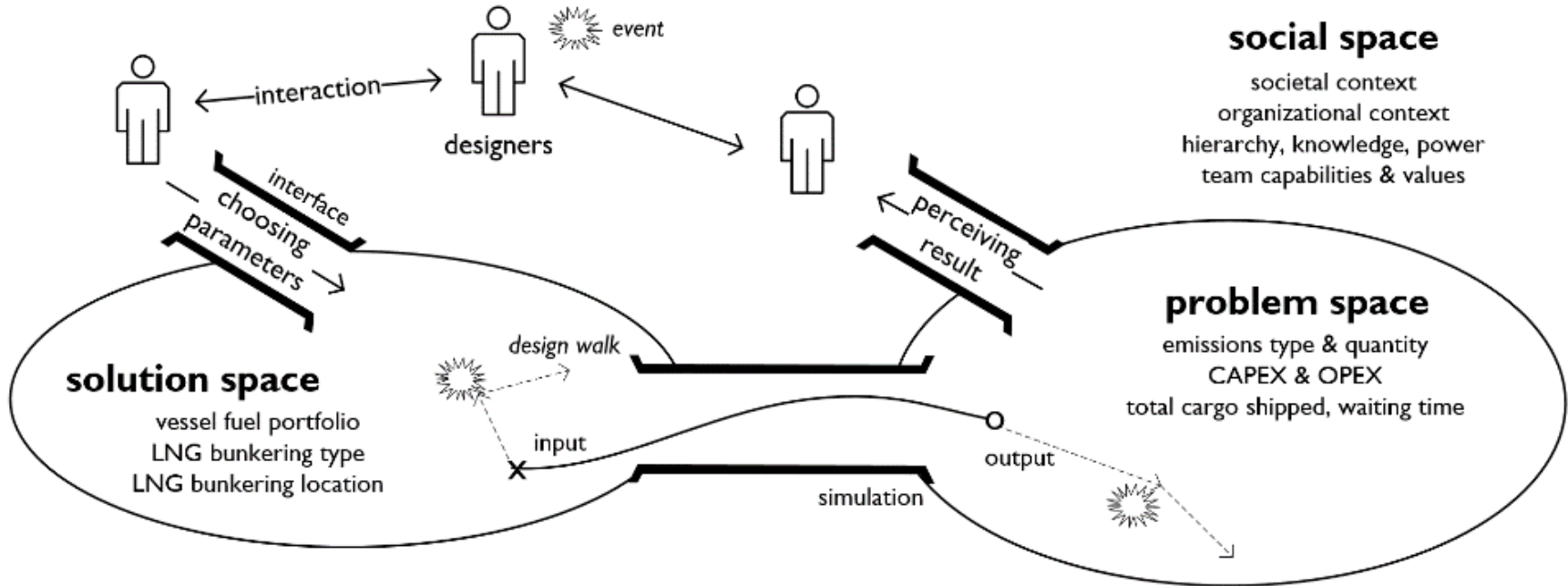
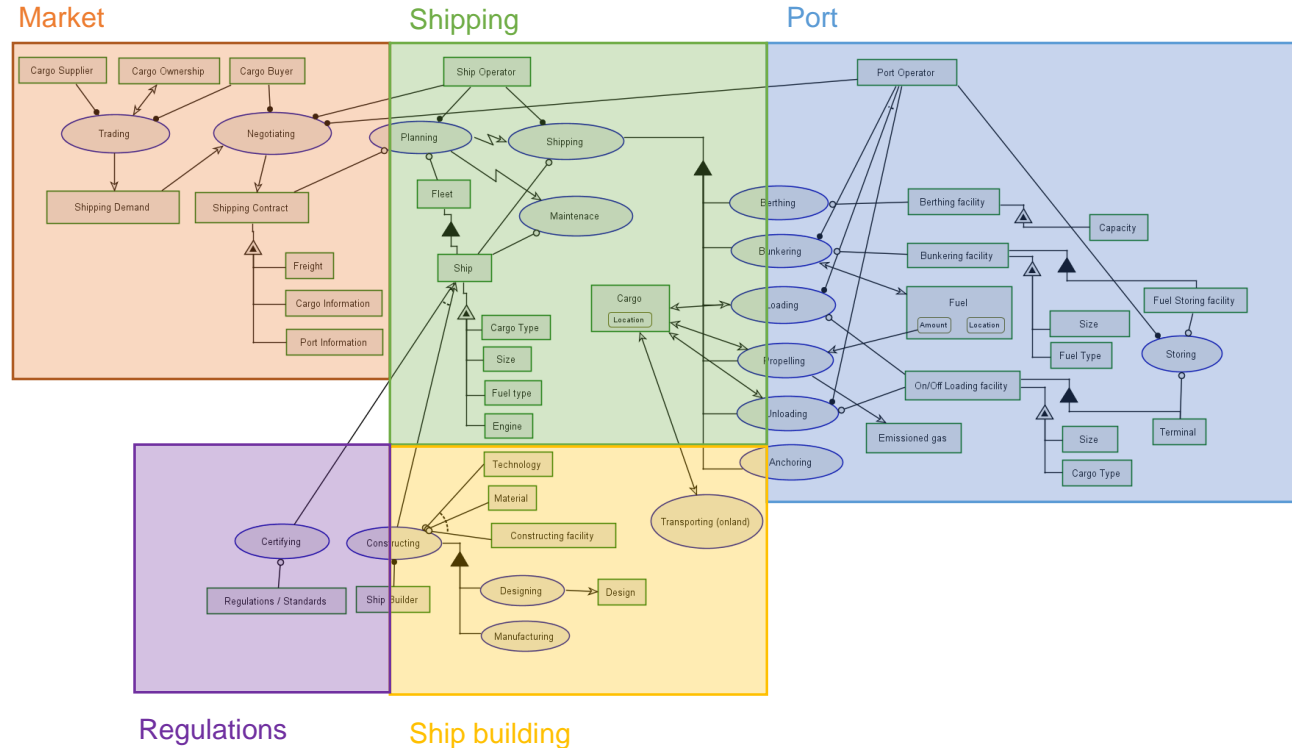


Fig. 1. A nomenclature for the design process, which consists of a design walk & events occurring simultaneously in the problem, solution, and social spaces - which forms the context for problem, solution & teamwork.

Challenge: Maritime Transition to New Fuels



An OPM systems model for this challenge, cutting across many actors in the maritime industry



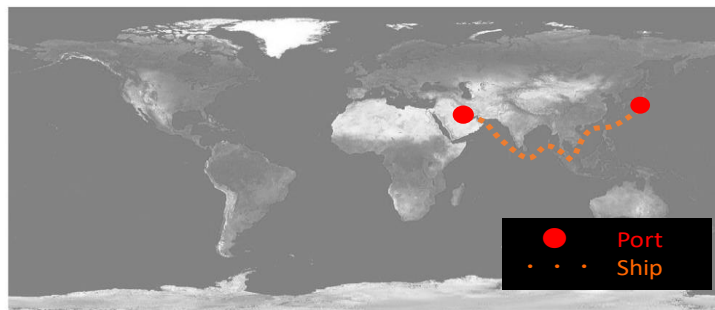
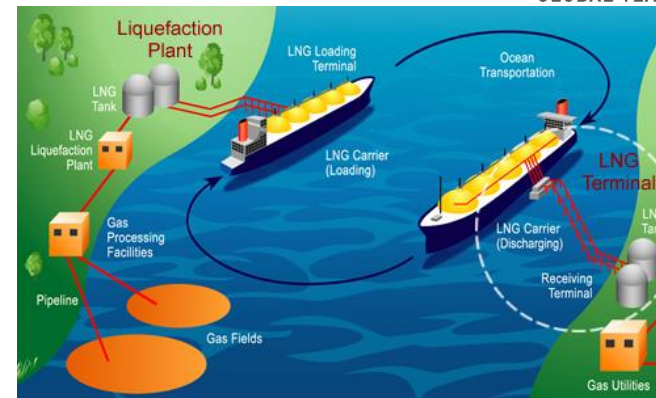
Lorena Pelegrin, Bryan Moser, Shinnosuke Wanaka, Marc-Andre Chavy-Macdonald, Ira Winder, "Field Guide for Interpreting Engineering Team Behavior with Sensor Data", *Complex Systems Design & Management (CSD&M) conference, December 2018, Paris, France*

Maritime Multi-Stakeholder Decisions for LNG



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Decision	Alternatives			
Number of Ships fueled with HFO	0	5	15	20
Number of Ships fueled with LSFO				
Number of Ships fueled with LNG				
Number of Ships fueled with HFO/LNG				
LNG Bunkering Location	Persian Gulf	Singapore	Japan	-
LNG Bunkering Method by Location	Truck to Ship	Ship to Ship	Shore to Ship	-
Number of LNG Bunkering Facilities by Location	0	1	3	-



Objective or -lility	Metric
Emissions Reduction	NOx Emissions [Ton/ Ton Cargo * km]
	SOx Emissions [Ton/ Ton Cargo * km]
	CO2 Emissions [Ton/ Ton Cargo * km]
Schedule	Waiting Time [%]
	Cargo Moved [Cargo Ton]
CAPEX	Initial Cost [MUSD]
OPEX	Fuel Cost Efficiency [USD/ Cargo Ton * km]

Instrumented Teamwork Experiment



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- Problem framework, key decisions, and info. on options provided
- Simulation and expert's judgement for evaluation of decisions
- Stages of individual and team discussions, decisions, interpretation
- Capture interactions with models and model changes
- Audio, Video, and Written communication among participants



UX + SysofSys Model + Instrumented Teamwork



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MaritimeDSS V1.0



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Process to Generate Narratives



Lorena Pelegrin, Bryan Moser, Shinnosuke Wanaka, Marc-Andre Chavy-Macdonald, Ira Winder, "Field Guide for Interpreting Engineering Team Behavior with Sensor Data", *Complex Systems Design & Management (CSD&M) conference, December 2018. Paris, France*

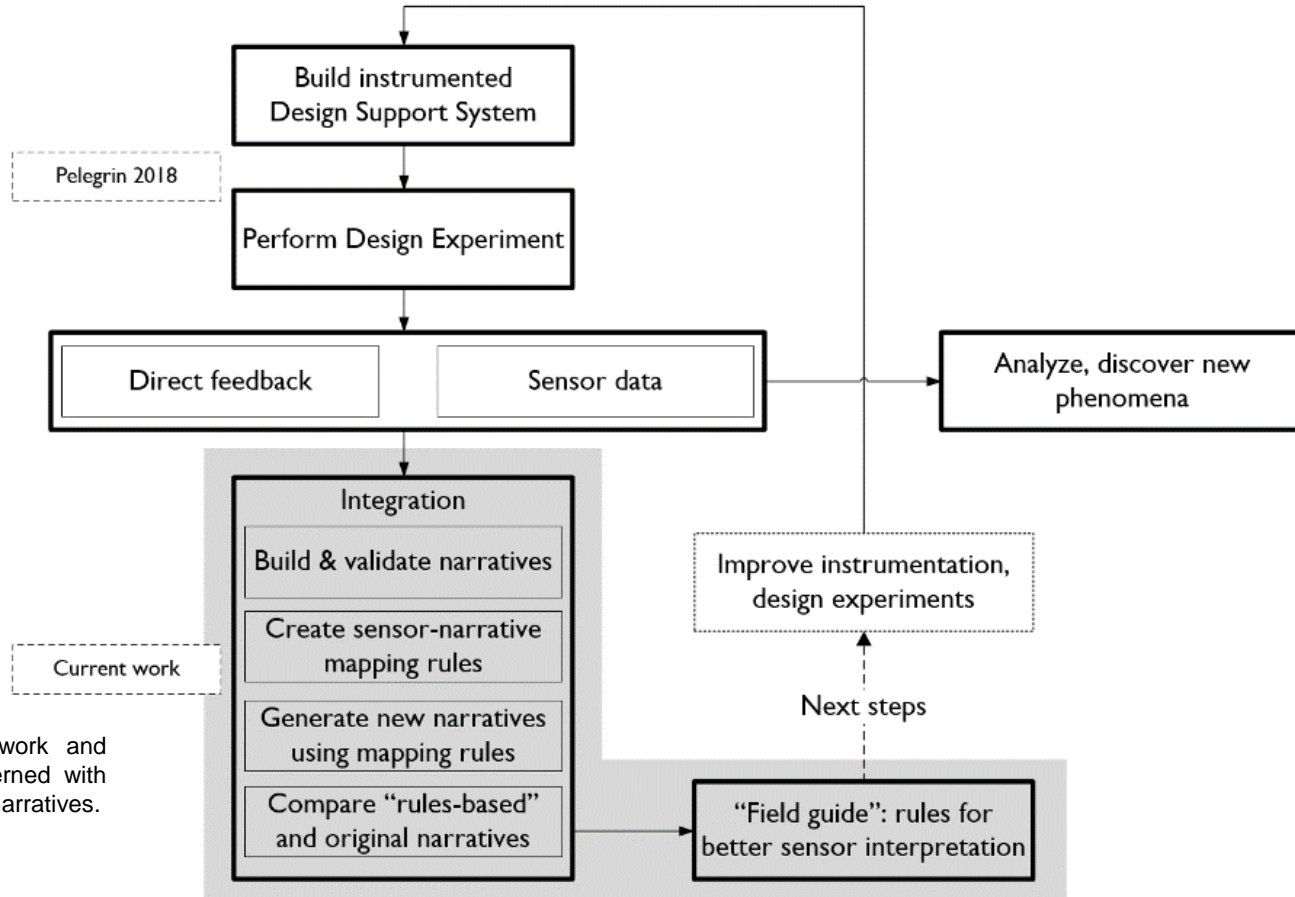


Fig. 3. Overview of the experimental framework and procedure. The current work is in grey, concerned with integrating data to generate holistic design walk narratives.

Experimental Framework



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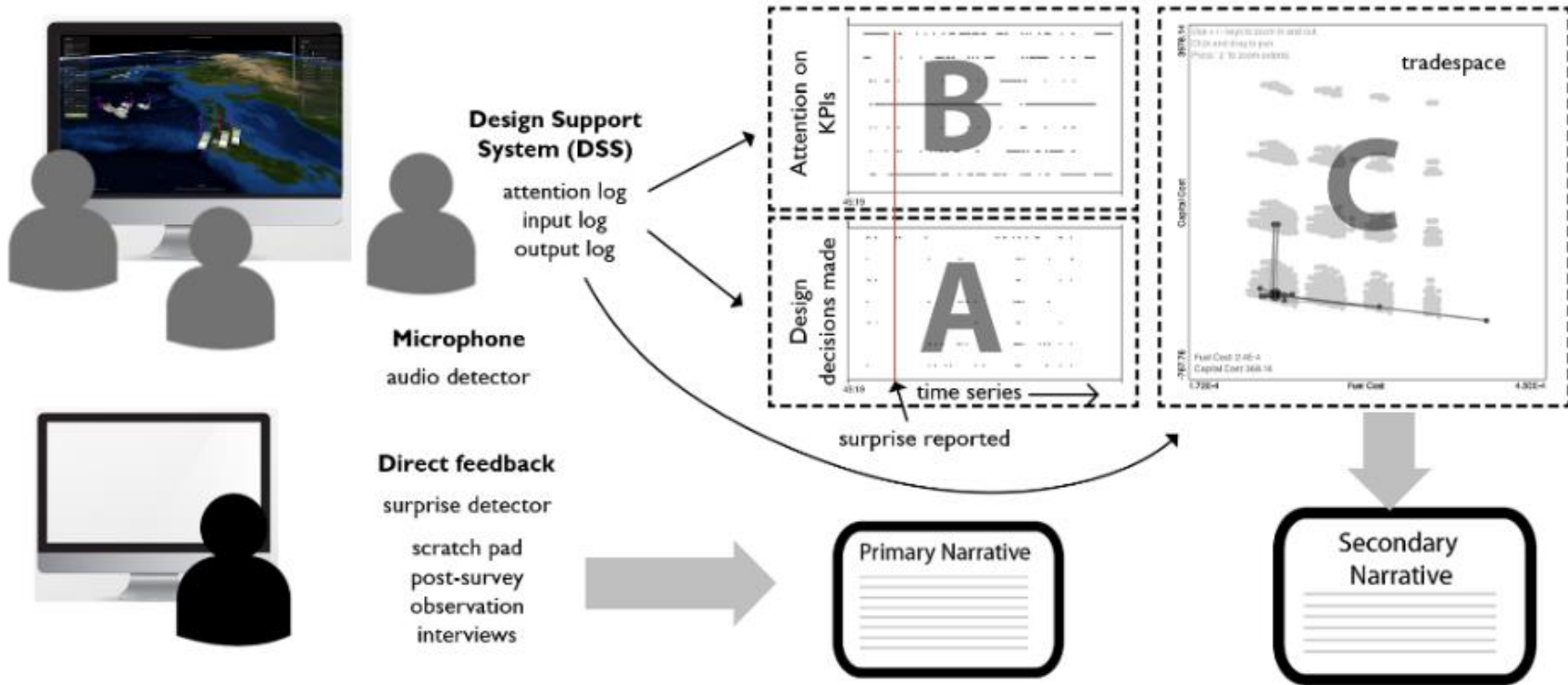


Fig. 2. A conceptual diagram of the experiment setup and research flow. During design experiments, sensors consist of DSS logs & microphones and “direct feedback” by human participants or observers. Sensor data is displayed, & both are interpreted into narratives.

Mapping rules (from sensor data to design walk narrative)



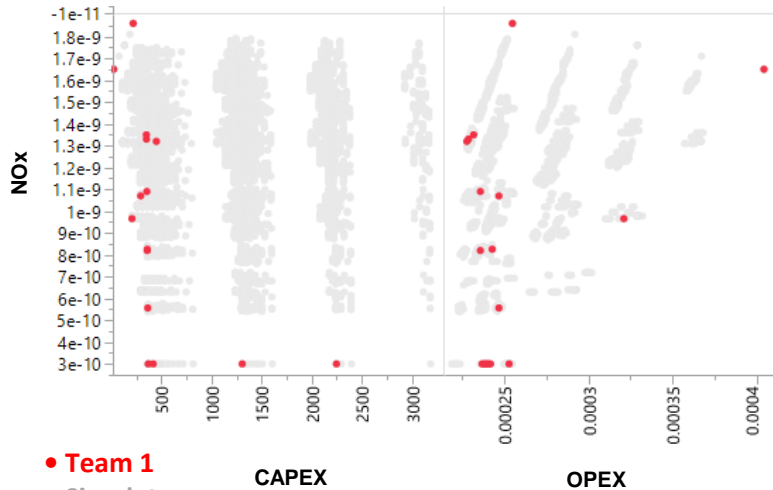
Narrative fragment	source of narrative	sensor / <i>proposed</i>	mapping rule / <i>proposed</i>
model confidence	comments from scratch sheet, post survey.	<i>surprise detector, input log</i>	<i>frequent or early surprises may indicate conflicting mental model: an input log showing OAT model factor</i>
prioritized preferences for decision	human - design rationale	<i>output log, attention log</i>	<i>avoided or preferred area of problem space: suspect key. Expected attention on key variable</i>
key surprises (learning) (e.g. “1 truck is enough!”)	human - scratch sheet comments (on surprises), post survey	<i>surprise detector, input log, output log, attention log</i>	<i>after surprise, “path dependent sequence”: marked change in behavior - use different input levers, attention, maybe output trends</i>
accidental result	combined output & attention logs	<i>attention log output log</i>	<i>good result, but no attention paid to this KPI in the log</i>

Decision Making Priorities



Narrative fragment	source of narrative	sensor / <i>proposed</i>	mapping rule / <i>proposed</i>
prioritized preferences for decision	human - design rationale	<i>output log, attention log</i>	<i>avoided or preferred area of problem space: suspect key. Expected attention on key variable</i>

Team	Which performance indicators did you individually consider more often during the design exercise?	Which performance indicators did your team discuss more during the design exercise?
Team 1-1	Emissions	OPEX
Team 1-2	Emissions	OPEX, Waiting Time, CAPEX
Team 1-3	OPEX, CAPEX	OPEX, CAPEX

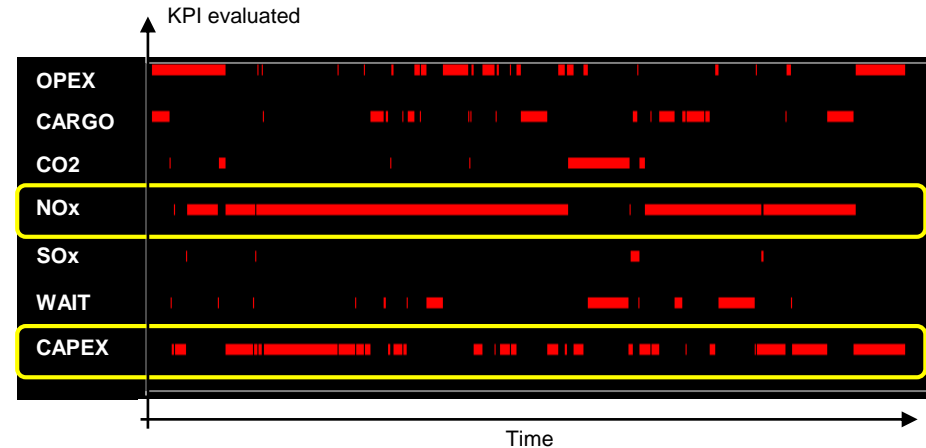


- Team 1
- Simulator

28%

79%

48%



Model Confidence



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Narrative fragment	source of narrative	sensor / proposed	mapping rule / proposed
model confidence	comments from scratch sheet, post survey, observation	<i>surprise detector, input log</i>	<i>frequent or early surprises may indicate conflicting mental model; an input log showing OAT model factor testing is low-confidence</i>

Arch. ID	Rationale	Surprises?	Reasons for Surprise and Comments
4	Bunkering moethod change to 1 bunker/truck to ship in JP/PG based on sample 2	Better performance than expected	Waiting time = 0...? Why?
5	Bunkering moethod change to 3 bunker/truck to ship in JP to ship based on sample 2 to decrease OPEX	Worse performance than expected	OPEX increases? Why?
6	Bunkering moethod change to 1 bunker/truck to ship in JP to ship based on sample 2 to decrease OPEX	Better performance than expected	OPEX decreases. BUT it indicates PG defined as JP in program because JP LNG > PG LNG. PG and JP is expected to be reversed.
8	Bunkering moethod change to 3 bunker/truck to ship in JP and 1 bunker/truck to ship in SIN based on sample 2 to decrease OPEX cost	Worse performance than expected	In program. PG=JP, JP=SIN, SIN=PG ??? Only LNG cost is swithed between JP (PG in program)/SIN
10	Bunkering method change to 3 bunker/truck to ship in SIN based on sample 2 to decrease OPEX cost	Worse performance than expected	What happened? Refuel doing in PG in visual. We should forget
11	Dual fueled ship, bunkering moethod change to 1 bunker/truck to ship in JP and 3 bunker/truck to ship in SIN to decrease OPEX and increase CAPEX	Better performance than expected	Cargo amount increases...

Time	Fuel				Bunkering				Surprise?		
	HFO fueled	LSFO fueled	LNG fueled	Dual fueled (# HFO)	# Bunker	Bunkering Method PG	# Bunker	Bunkering Method JP		# Bunker	Bunkering Method SG
14:51:28	20	0	0	0	0	0	0	0	0	0	
14:51:39	0	0	20	0	3	ShoreToShip	3	ShoreToShip	0	0	
14:52:49	0	0	20	0	1	ShipToShip	1	ShipToShip	0	0	
14:52:58	0	0	20	0	1	TruckToShip	1	TruckToShip	0	0	Surprise
14:57:33	0	0	20	0	1	ShipToShip	1	ShipToShip	0	0	
15:00:53	0	0	20	0	1	TruckToShip	1	TruckToShip	0	0	
15:02:00	0	0	20	0	3	TruckToShip	1	TruckToShip	0	0	Surprise
15:03:59	0	0	20	0	1	TruckToShip	3	TruckToShip	0	0	Surprise
15:06:11	0	0	20	0	3	TruckToShip	1	TruckToShip	0	0	
15:07:49	0	0	20	0	1	TruckToShip	3	TruckToShip	0	0	
15:08:18	0	0	20	0	1	TruckToShip	1	TruckToShip	0	0	
15:08:27	0	0	20	0	1	ShipToShip	1	ShipToShip	0	0	
15:08:40	0	0	20	0	1	TruckToShip	1	TruckToShip	0	0	
15:11:13	0	0	20	0	0	0	1	TruckToShip	1	TruckToShip	
15:16:04	0	0	20	0	0	0	3	TruckToShip	1	TruckToShip	Surprise
15:21:41	0	0	20	0	0	0	1	TruckToShip	3	TruckToShip	
15:22:57	0	0	20	0	0	0	0	0	3	TruckToShip	Surprise
15:24:18	0	0	20	0	0	0	1	TruckToShip	3	TruckToShip	
15:29:33	0	0	0	20	0	0	1	TruckToShip	3	TruckToShip	Surprise
15:35:27	0	0	0	20	0	0	1	TruckToShip	3	TruckToShip	
15:40:39	0	20	0	0	0	0	0	0	0	0	
15:43:43	0	0	10	10	0	0	1	TruckToShip	3	TruckToShip	
15:49:10	0	0	20	0	0	0	1	TruckToShip	3	TruckToShip	
15:49:18	0	0	0	20	0	0	1	TruckToShip	3	TruckToShip	
15:51:23	0	0	10	10	0	0	1	TruckToShip	3	TruckToShip	
15:53:21	0	0	10	10	0	0	3	TruckToShip	3	TruckToShip	
15:55:43	0	0	0	20	0	0	3	TruckToShip	3	TruckToShip	
15:56:27	0	0	0	20	0	0	1	TruckToShip	3	TruckToShip	
15:56:32	0	0	0	20	0	0	3	TruckToShip	3	TruckToShip	
15:58:48	0	0	20	0	0	0	3	TruckToShip	3	TruckToShip	
15:59:03	0	0	20	0	0	0	1	TruckToShip	3	TruckToShip	
15:59:19	0	0	20	0	0	0	3	TruckToShip	3	TruckToShip	
16:03:29	0	0	10	10	0	0	3	TruckToShip	3	TruckToShip	
16:04:09	0	0	10	10	0	0	1	TruckToShip	3	TruckToShip	
16:14:15	0	0	10	10	0	0	3	TruckToShip	3	TruckToShip	
16:14:33	0	0	20	0	0	0	3	TruckToShip	3	TruckToShip	
16:14:39	0	0	20	0	0	0	1	TruckToShip	3	TruckToShip	
16:16:16	0	0	20	0	0	0	3	TruckToShip	3	TruckToShip	
16:16:19	0	0	20	0	0	0	3	TruckToShip	1	TruckToShip	
16:16:56	0	0	20	0	0	0	3	TruckToShip	3	TruckToShip	
16:17:01	0	0	10	10	0	0	3	TruckToShip	3	TruckToShip	
16:17:30	0	0	10	10	0	0	3	TruckToShip	1	TruckToShip	
16:17:46	0	0	10	10	0	0	3	TruckToShip	3	TruckToShip	

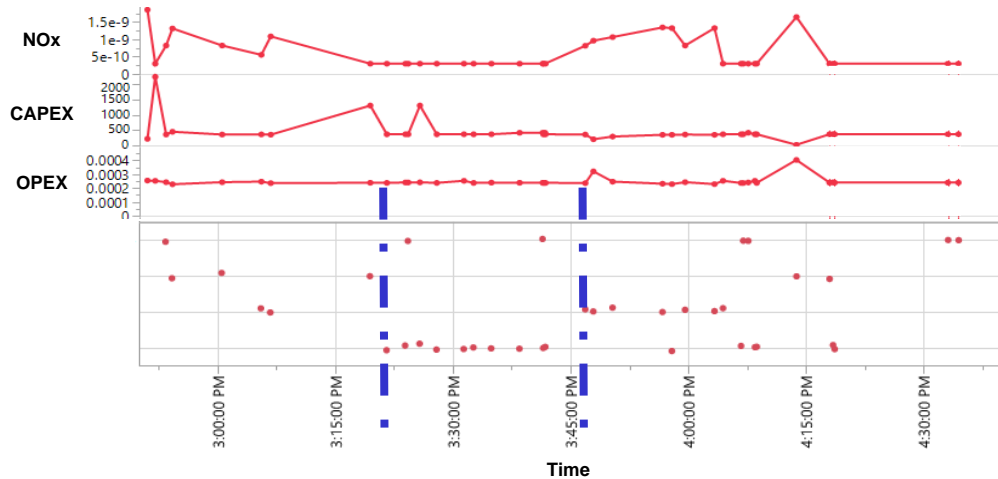
Phases of Design Walk



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Narrative fragment	source of narrative	sensor / <i>proposed</i>	mapping rule / <i>proposed</i>
phases of design walk	time series of aggregated input	input log, output log	look for pattern in input action "macro" time series, results

Time	Fuel				Bunkering					
	HFO fueled	LSFO fueled	LNG fueled	Dual fueled	# Bunkers PG	Bunkering Method PG	# Bunkers Japan	Bunkering Method JP	# Bunkers SG	Bunkering Method SG
14:50:00	20	0	0	0	0	0	0	0	0	0
14:51:00	0	0	20	0	3	ShoreToShip	3	ShoreToShip	0	0
14:53:23	0	0	10	10	1	TruckToShip	1	TruckToShip	0	0
14:54:12	0	0	0	20	1	ShipToShip	1	ShipToShip	0	0
15:00:32	0	0	10	10	1	TruckToShip	1	TruckToShip	0	0
15:05:32	0	0	15	5	1	TruckToShip	1	TruckToShip	0	0
15:06:44	0	0	5	15	1	TruckToShip	1	TruckToShip	0	0
15:19:26	0	0	20	0	0	0	0	0	3	ShoreToShip
15:21:33	0	0	20	0	0	0	0	0	1	TruckToShip
15:23:55	0	0	20	0	0	0	0	0	3	TruckToShip
15:24:16	0	0	20	0	0	0	0	0	3	TruckToShip
15:25:46	0	0	20	0	0	0	0	0	1	ShoreToShip
15:27:55	0	0	20	0	0	0	0	0	1	TruckToShip
15:31:23	0	0	20	0	1	TruckToShip	1	TruckToShip	0	0
15:32:37	0	0	20	0	0	0	0	0	1	TruckToShip
15:34:53	0	0	20	0	0	0	1	TruckToShip	1	TruckToShip
15:38:29	0	0	20	0	0	0	0	0	1	ShipToShip
15:41:26	0	0	20	0	0	0	0	0	1	ShipToShip
15:41:31	0	0	20	0	0	0	0	0	1	TruckToShip
15:41:43	0	0	20	0	0	0	0	0	1	ShipToShip
15:41:47	0	0	20	0	0	0	0	0	1	TruckToShip
15:46:52	0	0	10	10	0	0	0	1	1	TruckToShip
15:47:54	0	10	10	0	0	0	0	0	1	TruckToShip
15:50:21	10	0	10	0	0	0	0	0	1	TruckToShip
15:56:43	0	0	0	20	0	0	0	0	1	TruckToShip
15:57:55	0	0	0	20	1	TruckToShip	1	TruckToShip	0	0
15:59:36	0	0	10	10	1	TruckToShip	1	TruckToShip	0	0
16:03:21	0	0	0	20	1	TruckToShip	1	TruckToShip	0	0
16:04:26	0	0	20	0	1	TruckToShip	1	TruckToShip	0	0
16:06:44	0	0	20	0	1	TruckToShip	1	TruckToShip	1	TruckToShip
16:07:01	0	0	20	0	1	TruckToShip	1	TruckToShip	1	TruckToShip
16:07:39	0	0	20	0	1	TruckToShip	1	TruckToShip	1	ShipToShip
16:08:30	0	0	20	0	1	TruckToShip	1	TruckToShip	0	0
16:08:44	0	0	20	0	0	0	0	0	1	TruckToShip
16:13:48	0	20	0	0	0	0	0	0	0	0
16:18:01	0	0	20	0	1	TruckToShip	0	0	1	TruckToShip
16:18:27	0	0	20	0	0	0	0	0	1	TruckToShip
16:18:40	0	0	20	0	1	TruckToShip	0	0	1	TruckToShip
16:33:07	0	0	20	0	1	TruckToShip	0	0	1	TruckToShip
16:34:28	0	0	20	0	1	TruckToShip	0	0	1	TruckToShip



Learning

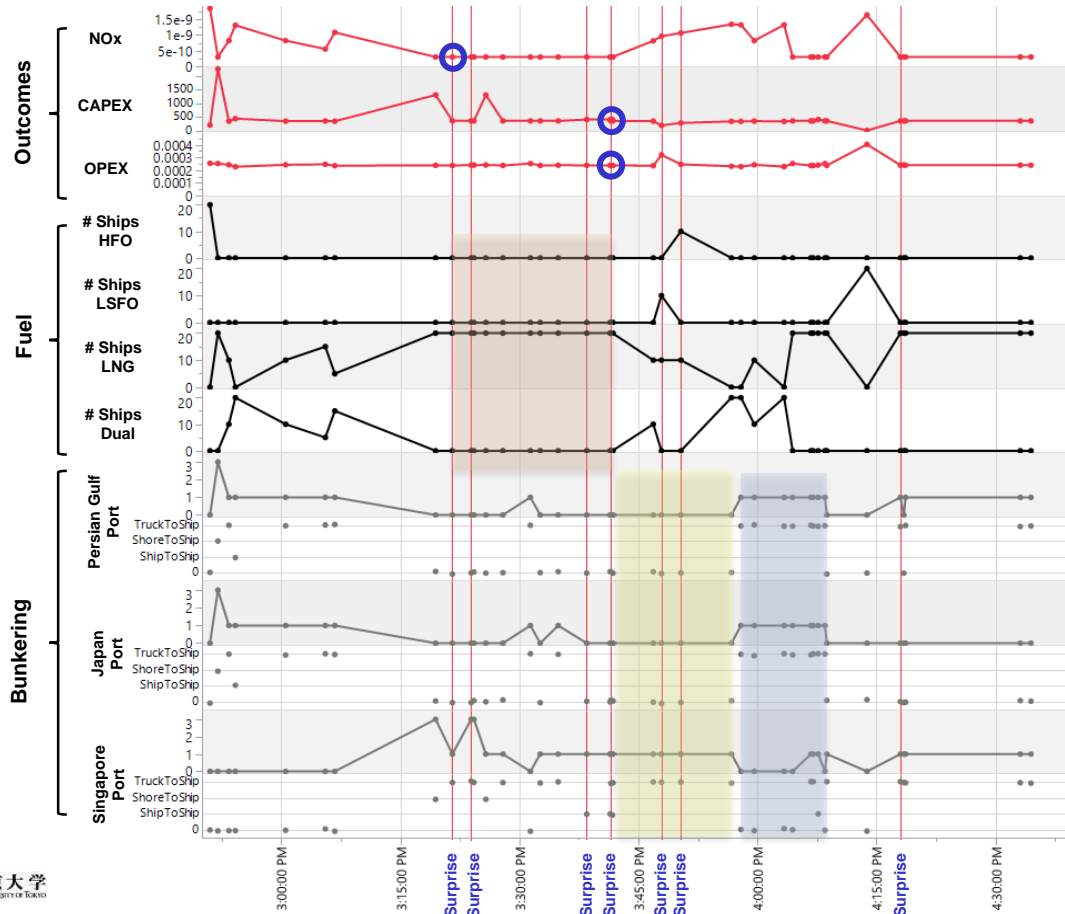


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narrative fragment	source of narrative	sensor / proposed	mapping rule / proposed
key surprises (learning)	human - scratch sheet comments (on surprises), post survey	surprise detector, input log, output log, attention log	after surprise, "path dependent sequence": marked change in behavior - use different input levers, attention, maybe output trends

Team No.-arch.	# Ships fueled with				Persian Gulf		Japan		Singapore	
	HFO	LSFO	LNG	Dual-fuel	# LNG Bunkers	Bunkering Method	# LNG Bunkers	Bunkering Method	# LNG Bunkers	Bunkering Method
Team 1			20		1	Truck to Ship			1	Truck to Ship

Surprise	Architecture		Recorded Reasons for Surprise	Potential Learning and likely decision in course of action
	ID	Configuration		
Surprise 1 (3:21pm)	09	20x LNG-fueled ships. 1x LNG Bunkers in SG, Truck-to-Ship	Better Emissions than anticipated	An LNG fleet works well. Bunkering choices might have limited effect on emissions. <ul style="list-style-type: none"> Continue exploring bunkering.



Narratives Example



Primary Narrative	Secondary Narrative
<p>This team interprets the design task literally: to reduce emissions at low cost, though are concerned at the lack of comparison of emissions to regulation. They also realize that waiting time should be considered, but decide to neglect the amount of cargo moved, because of unclear interpretation of this KPI. Thus they consider mostly NO_x, CAPEX and OPEX, checking other KPIs also.</p>	<p>From their attention to KPIs, the team's goal appears to be interpreted literally: reduce emissions at low cost, but keeping cargo moved nominal. However, emissions attention & outcomes are slightly less disciplined than for cargo moved and OPEX & CAPEX - the team may have made some minor change in goal emphasis (indeed, they often return to check NO_x later). But we see no clear sign of perceiving a goal or requirement to be ambiguous or unclear.</p>

+ Based on comments from scratch sheet, post survey, observation

+ Based on digital sensor data

Discussion: Overall Approach



- The **mapping rules & field guide** are to serve two purposes (Fig. 3): aid data interpretation, and improve experimental setup.
- the **most promising rules** may yield insight on prioritization, model trust, phases/modes of activity, and depth of surprise/learning.
- Some **sensor data may be *better* than direct** feedback - akin to "revealed preferences".
- For now, **ethnography and direct human feedback are still key to intent & the social space**, and to **validate** sensor-based narratives.
- Sensors for social space detection yet to be considered.

Lessons Learned



- + Capability to experiment by experimenting
 - + Loosely Constrained, Fluidly Evolving Experiments
 - + Real world, multi-actor, multi-attribute challenge
-
- Expand beyond surprises -- mental model development and validation.
 - Latency -- obtaining a new insight through surprise but not changing
 - Voice audio not experimentally successful (both implementation and analysis)

To expose dynamics of teamwork, a quasi-experiment to sense and transform data into team narratives was demonstrated:

- a experimental setup based on a **systems model and simulation** in the maritime industry for fuel transitions
- a formalized concept of a team **design walk narrative** and a taxonomy for **events in the problem, solution, and social spaces**
- workshops gather data applied to a set of **mapping rules** for transforming sensor data into a team narrative

Limitations: not a formally controlled experiment. Better interplay with classic primary (ethnography, survey) approaches needed.

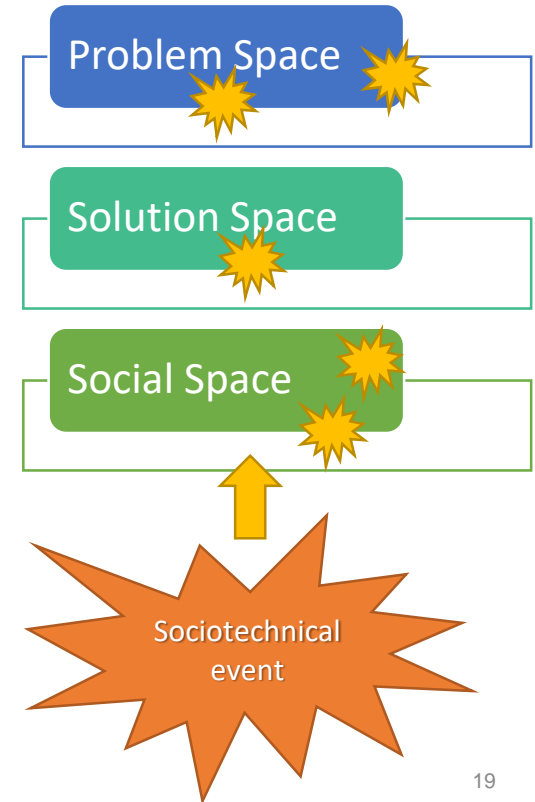


Platform, experiments and sensors

*Awareness – Attention – Decisions – Actions -
Interactions – Outcomes – Surprises – Learning*

To analyze events across teams as mapped to problem, solution, and social spaces.

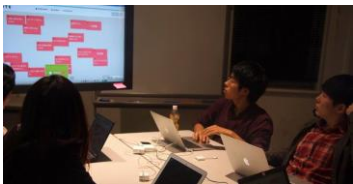
Our goal is real-time detection of framing and re-framing, unlearning and learning, and the overall health of *teams of teams* work during complex problem solving.



Summary of Recent Experiments



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Idea Generation

Agriculture



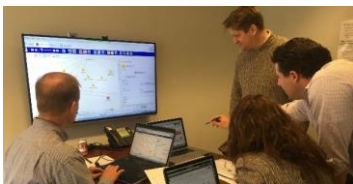
Model-Building
with Stakeholders

Urban
Environment



System
Architecture
Decisions

Maritime



Project Design

Automotive &
Aerospace

We're creating:

- platform for repeatable, teamwork experiments across multiple domains
- Sensors for attention and changes to models problem and solution
- reference measure and research protocols for phenomena at the (team of teams) meso-scale.

Just beginning

- To reach sufficient data to correlate performance outcomes to these exposed phenomena.

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