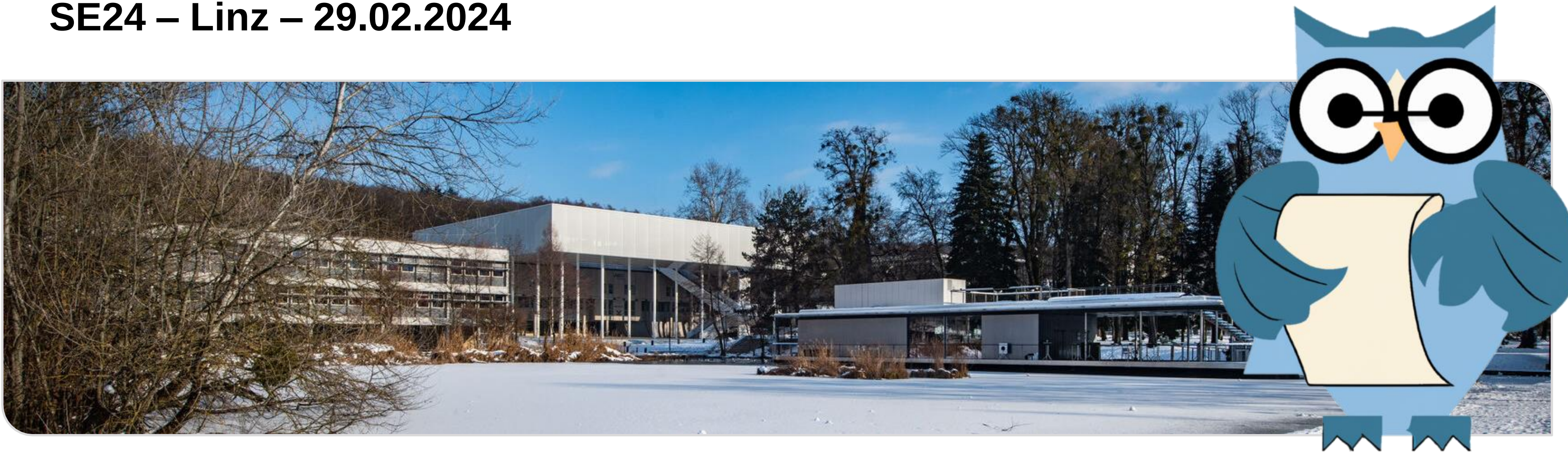
Karlsruhe Institute of Technology

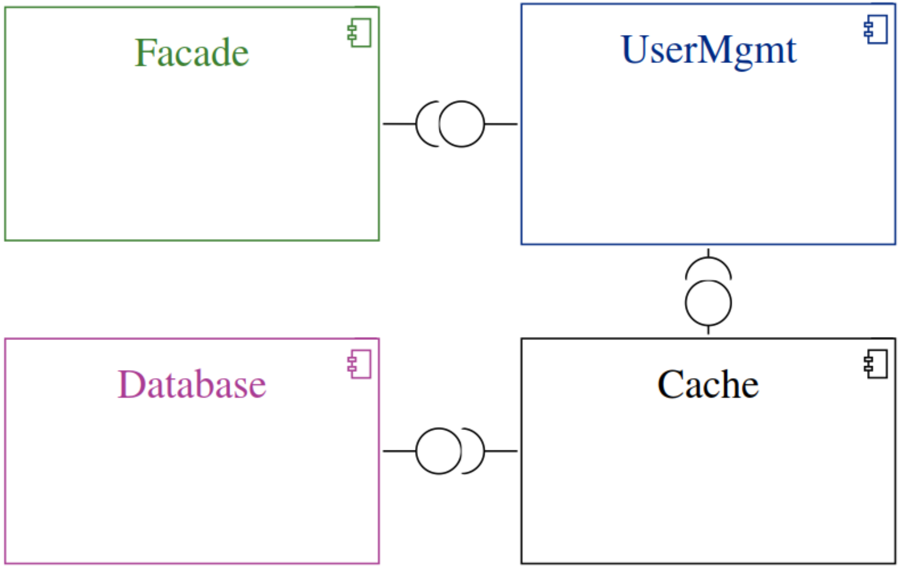
Detecting Inconsistencies in Software Architecture Documentation Using Traceability Link Recovery

Jan Keim, Sophie Corallo, Dominik Fuchß, Anne Koziolek

SE24 – Linz – 29.02.2024



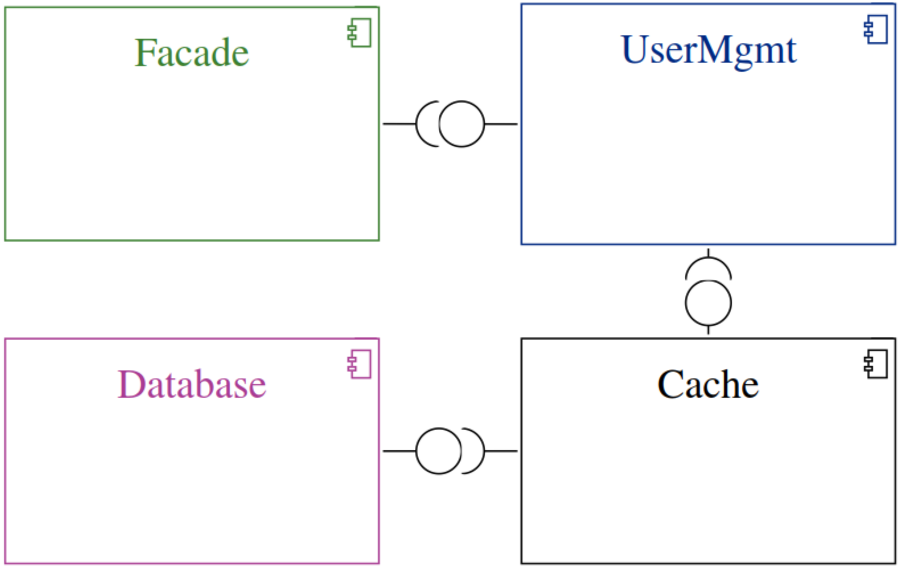
Software Architecture Documentation (SAD)



1) The system adheres to layered architecture.
2) The Facade is the entry point to the service.
3) It passes calls to the user management.
4) The user management then accesses the DB.
5) The Common component contains utility functionality.

Connecting SADs with Traceability Link Recovery

using the TLR approach SWATTR [Keim2021]



1) The system adheres to layered architecture.

2) The Facade is the entry point to the service.

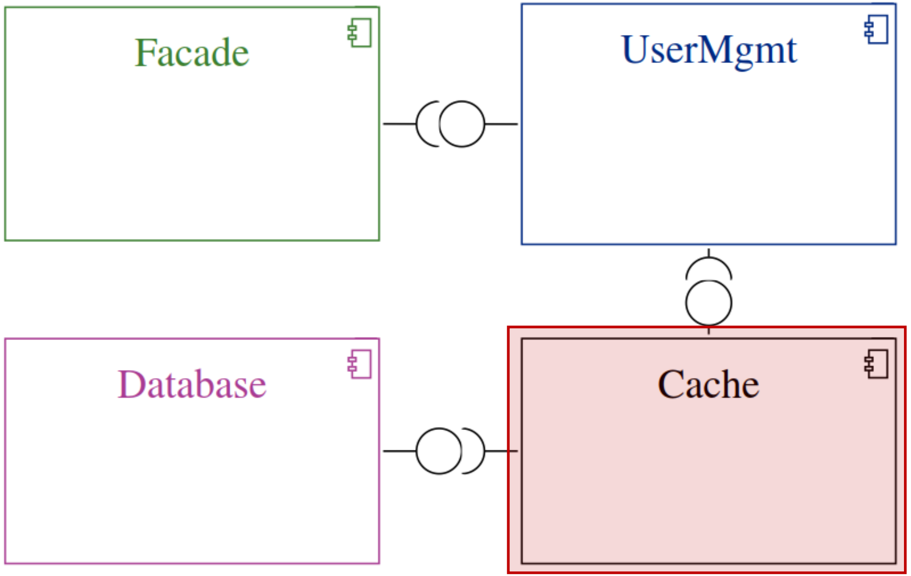
3) It passes calls to the user management.

4) The user management then accesses the DB.

5) The Common component contains utility functionality.

Unmentioned Model Elements

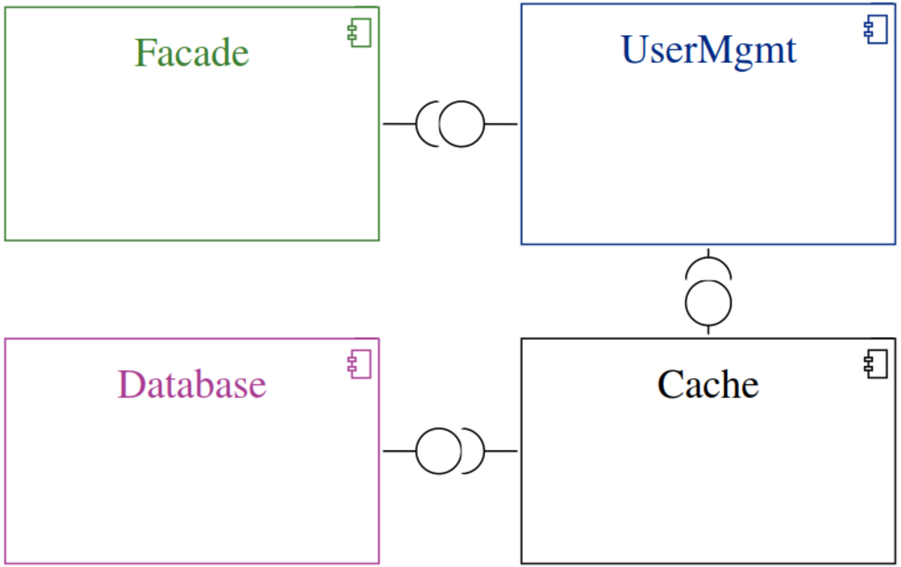
The model has an element that is not documented in the text



1) The system adheres to layered architecture.
2) The Facade is the entry point to the service.
3) It passes calls to the user management.
4) The user management then accesses the DB.
5) The Common component contains utility functionality.

Missing Model Elements

The text has an element that is not modelled



1) The system adheres to layered architecture.

2) The Facade is the entry point to the service.

3) It passes calls to the user management.

4) The user management then accesses the DB.

5) The Common component contains utility functionality.

Research Questions & Contributions

1) To what extent do changes to the previous approach SWATTR improve the performance for Traceability Link Recovery?
2) How does the approach perform for detecting unmentioned model elements?
3) How well does the approach detect missing model elements?

Contributions

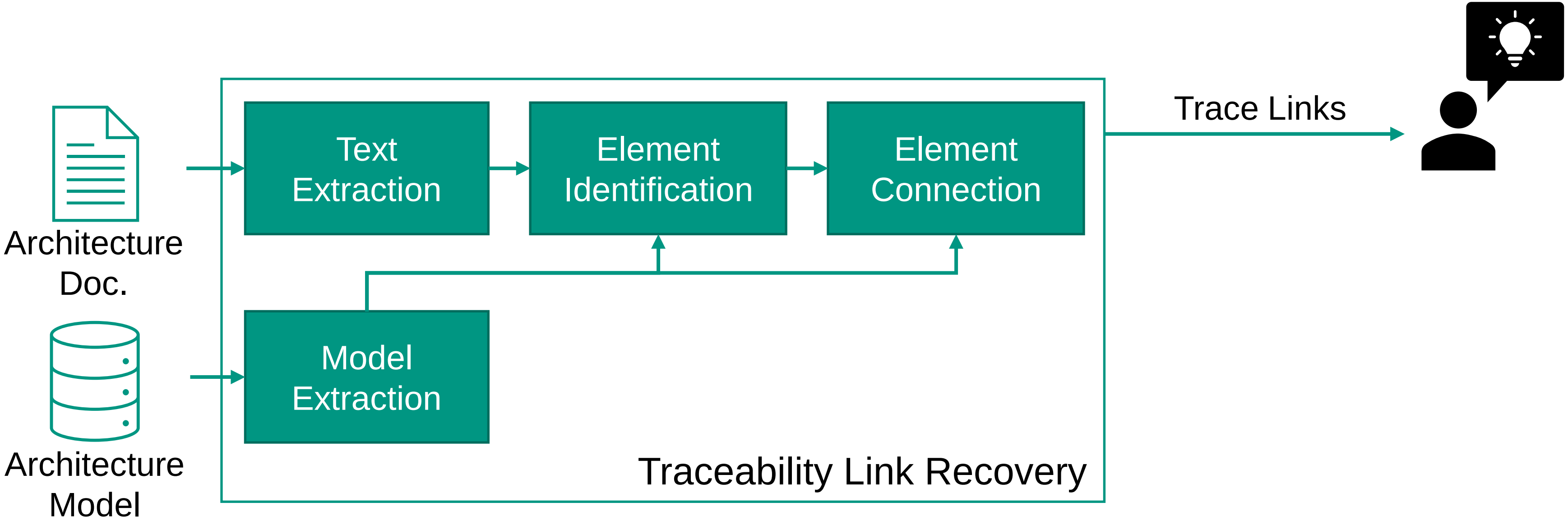
1. Extending TLR and add capabilities to identify inconsistencies
2. Novel approach (ArDoCo) to identify inconsistencies
3. Replication package

Related Work

- Inconsistency Detection between API/Code documentation and Code, e.g., Kim & Kim 2016
- Inconsistency Detection for requirements, e.g., Fantechi & Spinicci 2005, Kamalrudin et al. 2010
- Inconsistency Detection for Software Architecture, e.g., Lytra & Zdun 2014

No work looking at inconsistencies between
natural language software architecture documentations (NLSADs)
and software architecture models (SAMs)

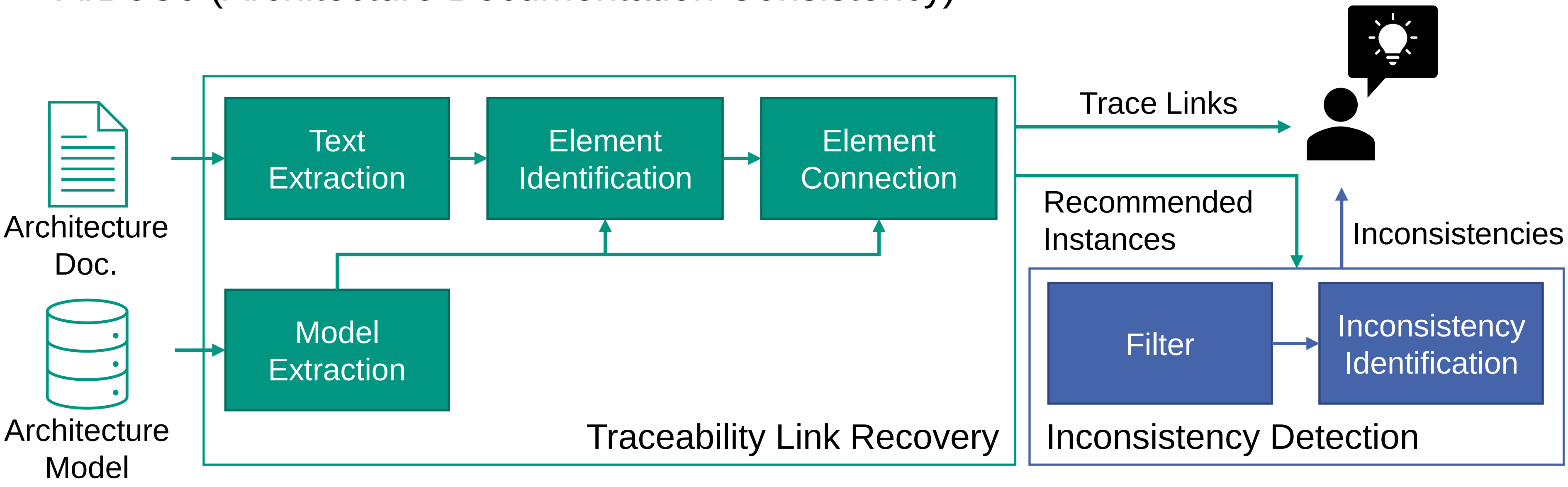
Background: SWATTR



[Keim2021]

Our Approach

ArDoCo (Architecture Documentation Consistency)



Detecting Unmentioned Model Elements

- Look for absent trace links for model elements (e.g., components)
- Each model element needs to have at least *one* trace link

- Configuration options to adjust to needs
  - Minimum number of needed trace links
  - Types of model elements that are checked (e.g., components, interfaces)
  - Regex-based whitelist

Detecting Missing Model Elements

- Make use of Recommended Instances (RIs) of SWATTR

→ RIs without a trace link are (potential) inconsistencies

- Problem: SWATTR detects many RIs to increase recall for TLR
- Therefore, filtering RIs based on
  - (dynamic) threshold regarding overall confidence
  - confidence for name and type of the RI
  - Number of occurrences
  - Unwanted words: general and project/domain-specific blacklists

Evaluation Projects

Project	Language (kLOC)		Forks	Contributors
MediaStore (MS)	Java	4	-	-
TeaStore (TS)	Java	12	0.1k	~ 15
TEAMMATES (TM)	Java	91	2.6k	~ 500
	TypeScript	54		
BigBlueButton (BBB)	JavaScript	69	5.8k	~ 180
	JSX	47		
	Scala	22		
	Java	21		
JabRef (JR)	Java	157	2.0k	~ 490

Current and historic versions of documentation used

Evaluation: Traceability Link Recovery

RQ1: To what extent do changes to the previous approach SWATTR improve the performance for TLR?

- Goals
  - To measure how well we can link sentences that mention a certain model element to the model elements
  - To compare the results
- Process
  - Comparison with gold standard

- Metrics
  - Precision, Recall, F1 – Score
  - Accuracy, Specificity
  - Φ – Coefficient
  - Average, Weighted Average

Evaluation: Comparing TLR results

- Baseline Approach
  - Assumption: Elements that should be linked have equal or similar naming
  - Extracts n-grams for sentences and model elements (n = {1,2,3})
  - Compares n-grams from text and models using normalized Levenshtein distance
  - Create Trace Links if comparison shows (high) similarity

Approach	Precision*	Recall*	F1-Score*	Accuracy*
Baseline	.80	.37	.50	.89
SWATTR	.49	.63	.52	.94
ArDoCo	**.81**	**.81**	**.80**	**.98**

* weighted Average

Evaluation: Inconsistency Detection - UMEs

RQ2: How does the approach perform for detecting unmentioned model elements?

- Goal
  - To measure how well we can detect unmentioned model elements
- Process
  - Comparison with gold standard

- Metrics
  - Precision, Recall, F1 – Score
  - Accuracy, Specificity
  - Φ – Coefficient
  - Average, Weighted Average

Evaluation: Inconsistency Detection - UMEs

Project	# Elements		Precision		Recall		F1-Score		Accuracy	
MS		4		.67		1.0		.80		.88
TS	6	5	1.0	1.0	.83	1.0	.91	1.0	.91	1.0
TM	1		1.0		1.0		1.0		1.0	
BBB	4	1	.50	1.0	.75	1.0	.60	1.0	.73	1.0
JR	3	1	1.0	1.0	.67	1.0	.80	1.0	.83	1.0
w. Avg.			.86	.88	.79	1.0	.80	.93	.85	.95
			.87		.88		.86		.90	

■ Historic

■ Current

Evaluation: Inconsistency Detection - MMEs

RQ3: How well does the approach detect missing model elements?

- Goals
  - To measure how well the approach detects missing model elements
  - To compare with a simple baseline
  - To measure the influence of filter lists
- Process
  - Remove model elements to create (artificial) inconsistencies

- Metrics
  - Precision, Recall, F1 – Score
  - Accuracy, Specificity
  - Φ – Coefficient
  - Average, Weighted Average

Evaluation: Inconsistency Detection - MMEs

Project	Precision		Recall		F1-Score		Accuracy	
MS		.21		.79		.33		.70
TS	.16	.96	.98	.70	.28	.79	.38	.96
TM	.17	.18	.63	.76	.26	.28	.86	.85
BBB	.09	.89	.18	.46	.11	.43	.81	.96
JR	.22	1.0	.11	.44	.15	.44	.57	.85
w. Avg.	.14	.60	.47	.63	.19	.43	.71	.87
	.39		.64		.34		.77	

▨ Historic

🟦 Current

Discussion

- Good results, some outliers
- Outliers when text and model diverge too much → Low precision

- Threats to Validity
  - Few open-source cases, unclear how well this generalizes
  - Artificial inconsistencies introduced when evaluating MME-detection
  - Benchmark dataset with potentially biased gold standards

Conclusion

- We investigated automatic detection of inconsistencies in software architecture documentation using trace links
- We improved the approach for TLR and proposed an approach to identify missing model elements and unmentioned model elements

- We evaluated using five projects
  - TLR: F1-Score 0.81, Accuracy 0.98
  - ID – UMEs: F1-Score 0.89, Accuracy 0.93
  - ID – MMEs: F1-Score 0.39, Accuracy 0.77
  - Outperforming baselines
- Needed Improvements & Future Work
  - Make use of relations and check their consistency
  - Experiment with deep learning/language models

Resources at ardoco.de/c/icsa23

References

- [Keim2021] J. Keim, S. Schulz, D. Fuchß, C. Kocher, J. Speit, and A. Koziolek, “Tracelink recovery for software architecture documentation,” in Software Architecture, S. Biffl, E. Navarro, W. Löwe, M. Sirjani, R. Mirandola, and D. Weyns, Eds. Springer International Publishing, 2021, pp. 101–116.
- [KimKim2021] S. Kim and D. Kim, “Automatic identifier inconsistency detection using code dictionary,” Emp. Softw. Engg., vol. 21, no. 2, p. 565–604, 2016.
- [FantechiSpinicci2005] A. Fantechi and E. Spinicci, “A content analysis technique for inconsistency detection in software requirements documents.” 2005, pp. 245–256.
- [Kamalrudin2010] M. Kamalrudin, J. Grundy, and J. Hosking, “Managing consistency between textual requirements, abstract interactions and essential use cases,” in IEEE Annual Computer Software and Applications Conference, 2010, pp. 327–336.
- [LytraZdun2014] I. Lytra and U. Zdun, “Inconsistency management between architectural decisions and designs using constraints and model fixes,” in 2014 23rd Australian Software Engineering Conference, 2014, pp. 230–239.