

MECHANISM FOR TRANSFER OF INDUSTRIAL DIGITAL TWINS TO SMART CITY INFRASTRUCTURE

OLHA PROKOPENKO^{1*}, TALIA T BIELIALOV², VITALIY OMELYANENKO³,
MILENA KIRILOVA FILIPOVA⁴, JULIA ROSEND⁵

¹Estonian Entrepreneurship University of Applied Sciences, Tallinn, Estonia; Armenian State University of Economics, Yerevan, Armenia; Department of Business Economics and Administration, Sumy State Makarenko Pedagogical University, Sumy, Ukraine.

²Department of Entrepreneurship and Business, Kyiv National University of Technologies and Design, Kyiv, Ukraine.

³Department of Problems of Innovation and Investment Development of Industry, Institute of Industrial Economics of the National Academy of Sciences of Ukraine, Kyiv, Ukraine.

⁴Southwest University Neofit Rilski, Blagoevgrad, Bulgaria.

⁵RDI Department, Estonian Entrepreneurship University of Applied Sciences, Tallinn, Estonia.

E-mail: ¹olhaprokopenko@eu-science.org, ²taliat_bielialov@ukr.net, ³omelyanenko.v@gmail.com, ⁴kirilova_milena@gmail.com, ⁵julia.rosend@eek.ee

ABSTRACT

Introduction: Digital twins are increasingly used to manage complex urban infrastructure. At the same time, the transfer of industrial models to smart city environments remains poorly formalized. This necessitates verification of the semantic-adaptive approach to their deployment.

Purpose: The aim of the study is the laboratory-based verification of the preservation of states, functions, fault logic, KPIs, and decision-support values during the deployment of an industrial digital twin in an urban cyber-physical environment.

Methods: The methodology was based on a reproducible laboratory verification of the transfer between a digital twin of a MathWorks Simscape Triplex Pump pumping unit and a digital twin of a DHALSIM urban water supply network. Structural and parametric analysis determined the suitability of parameters, fault classes, and functions for urban deployment. Comparative model mapping compared direct transfer with functional transformation of fault logic. Semantic-adaptive deployment provided semantic adaptation of parameters, states, functions and KPIs of the pump digital twin to the urban infrastructure environment. Multi-criteria evaluation and statistical testing compared the digital twin transfer mechanisms (M1, M2 and M3) in terms of transfer quality. The analytical environment was implemented in Python using pandas, NumPy, SciPy, statsmodels, and matplotlib.

Results. Transfer quality depended on preserving model logic rather than only transferring parameters. IUDTTI increased from 0.46 for M1 Direct Parameter Transfer to 0.88 for M3 Semantic-Adaptive Model Deployment. ANOVA showed a statistically significant difference between the mechanisms: $F(2,12) = 38.6$; $p < 0.001$; $\eta^2 = 0.86$. These findings support the laboratory advantage of semantic-adaptive transfer over direct parametric transfer. Practical reuse of industrial twin modules remains subject to field validation.

Conclusion: The scientific contribution is a semantic-adaptive transfer mechanism that extends transfer beyond parameters to state models, function models, event logic, and KPI semantics. Future work requires field testing on real urban sites, heterogeneous assets, and more complex operating scenarios.

Keywords: *Semantic Compatibility, Cyber-Physical Environment, Risk Scenarios, Functional Integrity, Maintenance, Hydraulic Simulation, Interoperability*

1. INTRODUCTION

Relevance of the research. Digital twins are gradually moving from industrial modelling to urban management as part of the broader digital transformation of the economy and infrastructure [1]. This increases the need for mechanisms for their

cross-domain use [2, 3]. In smart cities, the digital twin is already considered as a monitoring, forecasting, and decision support tool. However, its effectiveness depends on the ability to combine different infrastructure models [4, 5]. The transfer of digital twins to the civil infrastructure environments is of particular importance. Here, not only data but

also functions, states, and response scenarios become important [6].

For industrial systems, digital twins already have a developed technical base. However, their reuse in urban environments requires additional adaptation [7, 8]. The transfer relies on the Internet of Things (IoT), Cyber-Physical Systems (CPS), simulation tools, and interoperable architectures. These technologies connect physical assets with digital environments [9]. Cyber-physical systems further support the integration of industrial models into complex urban settings [10, 11]. Therefore, this study examines the transition from an isolated industrial twin to a deployable urban module.

Research gap. Current research on digital twins mainly considers industrial and urban models separately. The transfer of a ready-made Industrial Digital Twin to an Urban Digital Twin environment is less researched. Existing approaches more often describe data exchange, interoperability or visualization. At the same time, the preservation of states, functions, fault logic and KPIs after deployment is not sufficiently explained. This creates a gap in terms of reusing industrial twin modules in smart city infrastructure.

Problem statement. The main problem is the limitation of direct transfer of parameters between digital twins. Such a transfer can preserve signals, but lose the functional content of the model. The industrial twin contains diagnostic states, failure scenarios and predictive functions. In the urban context, these elements should be transformed into service risks. Therefore, a mechanism for adaptive deployment of the Industrial Digital Twin in the Urban Digital Twin is needed. The study considers Functional Wrapping Transfer as a functional transfer, in which not only parameters but also operational functions are transferred between digital twins, in particular monitoring, anomaly detection, fault classification, degradation assessment, and predictive maintenance.

Research questions. RQ1. To what extent is the Industrial Digital Twin suitable for deployment in an Urban Digital Twin environment? RQ2. How do Direct Parameter Transfer, Functional Wrapping Transfer, and Semantic-Adaptive Model Deployment differ? RQ3. Does semantic-adaptive deployment improve the quality of transfer compared to direct transfer? RQ4. What factors most affect the efficiency of transferring an Industrial Digital Twin to an urban environment?

Research hypothesis. H1 proposes that Semantic-Adaptive Model Deployment provides higher

transfer quality than direct parametric transfer because it jointly preserves state meaning, functional logic, scenario interpretation, and decision-support value. The hypothesis is tested through IUDTTI and scenario-level statistical comparisons.

The aim of the research is the development and laboratory testing of an approach to deploying an industrial digital twin in an urban cyber-physical environment. The research is aimed at assessing how states, functions, fault logic, KPIs and decision support value are preserved after such deployment. Special attention is paid to the comparison of direct parametric transfer, functional wrapping, and semantic-adaptive adaptation.

Research objectives:

- verify the suitability of Industrial Digital Twin for deployment in Urban Digital Twin environment;
- determine parametric, functional and scenario correspondences between Simscape Triplex Pump, and DHALSIM (Digital HydrAuLic SIMulator,) AnyTown urban water supply network (DHALSIM test configuration);
- compare the transfer mechanisms of digital twins (M1, M2 and M3) in terms of the quality of fault logic, functions, and urban scenarios;
- statistically evaluate the transfer efficiency in terms of semantic compatibility, functional integrity, interoperability, and IUDTTI.

2. LITERATURE REVIEW

A review of relevant studies shows that digital twins are gradually moving from technical simulation to infrastructure management. The issue of reusing industrial twin models in an urban environment is becoming particularly important. In this context, model compatibility, function preservation, scenario adaptation, and connection to decision-support procedures are key.

The initial understanding of the digital twin was formed in the engineering field, where the main thing was to reproduce the behaviour of a complex object. Glaessgen and Stargel [12] considered the digital twin as a basis for predicting the state of aviation systems. Rosen et al. [13] shifted the emphasis to the autonomy of production systems. Kritzinger et al. [14] clarified the difference between digital model, digital shadow, and digital twin. Together, these studies showed that a simple digital representation is not yet a full-fledged twin mechanism.

Further development of the concept has strengthened the connection between the digital twin, data, and service logic. Tao et al. [15] proved the importance of big data for the design, production, and maintenance of products. Fuller et al. [16]

systematized technologies, integration problems, and open research questions. At the same time, digital transformation promotes the integration of digital technologies into the management processes of complex socio-economic systems and creates the prerequisites for the wider use of digital models in various subject areas [17]. In parallel, digital modelling is more often considered as a tool for supporting management decisions and predicting the development of complex systems [18]. Ferré-Bigorra et al. [19] moved the discussion to the city level, showing the potential of digital twins for the management of urban infrastructure. Therefore, the digital twin gradually became not only a model of the object, but also an environment for managerial interpretation.

In the field of water infrastructure, research is already approaching applied problems, but remains largely domain-locked. Ramos et al. [20] linked smart water grids with digital twins to improve the efficiency of water distribution networks. Ostfeld and Abhijith [21] substantiated the digital twin as a new management paradigm for water distribution systems. Singh et al. [22] proposed a framework for detecting leaks in large-scale water networks. These results are important, but they mostly work in the water supply domain. The issue of transferring the industrial pumping model to the urban water twin remains poorly addressed.

More recent studies expand the scope of the problem but do not close the gap between industrial and urban twins. Azadi et al. [23] examine the planning and decision-support role of urban digital twins. Ghorbani Bam et al. [24] synthesize water-sector applications, while Hiller et al. [25] assess urban digital-twin maturity. These studies clarify application domains and implementation conditions, but they do not specify how a ready industrial twin should preserve diagnostic functions, fault logic, and KPI meaning after runtime integration into an urban twin.

Taken together, the literature shows a progression from object-level models to infrastructure-oriented digital twins. However, three limitations remain. First, interoperability research largely classifies barriers or levels rather than executing cross-domain model deployment. Second, urban frameworks emphasize data integration and decision support without testing preservation of industrial fault logic. Third, water-sector studies usually build or operate domain-specific twins rather than reuse a pre-existing industrial twin module. These limitations define the methodological gap addressed in this study.

Critical synthesis. Recent interoperability studies reinforce this gap. Acharya et al. [29, 31] and Memon et al. [30] formalize interoperability barriers, levels, and context dependence. Klar et al. [32], Karabulut et al. [33], and Adreani et al. [34] emphasize maturity, ontologies, and heterogeneous data integration. These approaches support connectivity, but they do not test a sequential transfer chain that preserves model behaviour during runtime deployment. Water-distribution studies [39–41] move closer to operation, yet they mainly construct or update urban twins from field data. The reverse path—adapting a ready industrial twin into an urban functional module—remains insufficiently examined.

Problem statement. The unresolved problem is how to deploy an existing Industrial Digital Twin inside an Urban Digital Twin without reducing the transfer to signal exchange. Direct parameter matching may preserve pressure or flow values, but it can lose state semantics, diagnostic functions, fault logic, KPI meaning, and service relevance. Therefore, this study treats transfer as model-behaviour deployment and tests whether semantic, functional, and simulation adaptation can preserve these elements.

Research questions. RQ1. To what extent is the Industrial Digital Twin suitable for deployment in an Urban Digital Twin environment? RQ2. How do Direct Parameter Transfer, Functional Wrapping Transfer, and Semantic-Adaptive Model Deployment differ? RQ3. Does semantic-adaptive deployment improve transfer quality compared with direct and functional transfer? RQ4. Which transfer properties most strongly explain the resulting IUDTTI variation?

Research hypothesis and objective linkage. H1 states that Semantic-Adaptive Model Deployment will provide higher transfer quality than M1 and M2 because it jointly preserves semantic compatibility, functional integrity, scenario coverage, and interoperability. These questions define the four study objectives: assess transfer readiness; establish parametric, functional, and scenario correspondences; compare M1–M3; and statistically test transfer efficiency. Thus, the objectives follow directly from the limitations identified in the reviewed studies.

3. MATERIALS AND METHODS

3.1 Research Procedure

The research design. The applied research design (Figure 1) was determined by the need to verify the

digital twin transfer mechanism not on an abstract scheme, but in a controlled engineering environment. An industrial pump model, a city water distribution twin, and a fixed deployment point were combined for this purpose. This design made it possible to consistently assess the suitability of the model, the quality of the transfer, the preservation of functional logic, and the statistical stability of the results. The design also ensured reproducibility, as all operations were performed within defined

models, scenarios, and metrics. This made it possible to compare direct parameter transfer, functional wrapping, and semantic-adaptive unfolding in the same laboratory conditions. In this study, laboratory testing means an experimental assessment of the transfer mechanism in a controlled digital environment without operational field data.

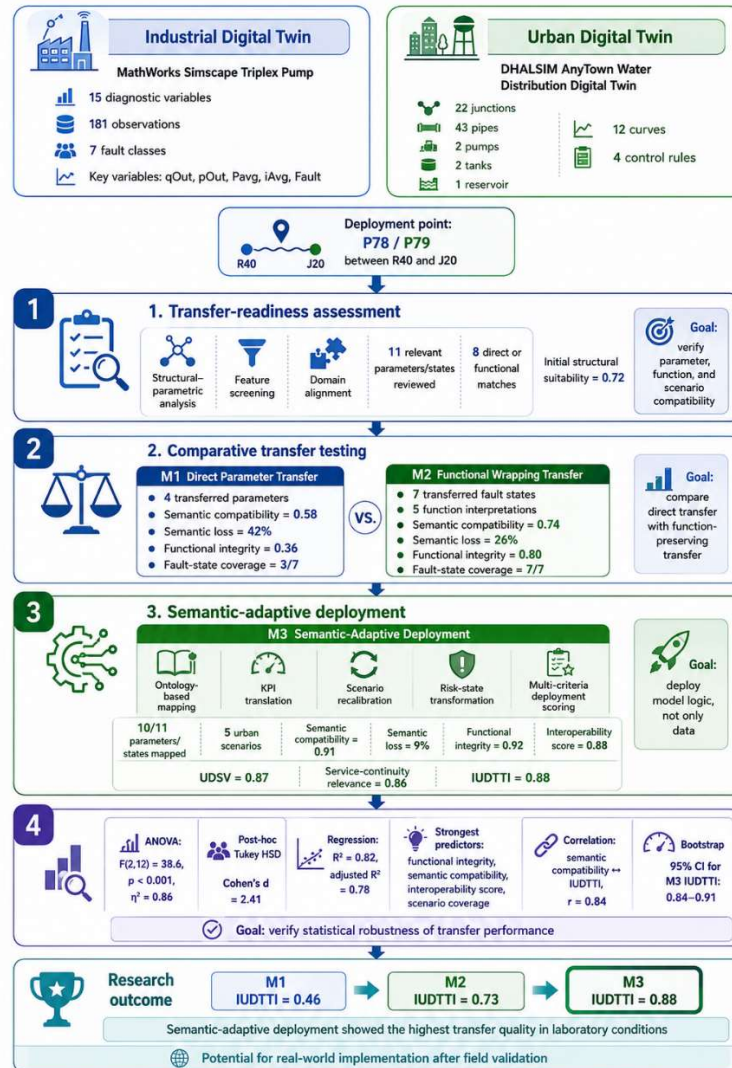


Figure 1: Design procedure for laboratory testing of semantic-adaptive transfer of Industrial Digital Twin to Urban Digital Twin

Source: developed by the authors

3.2 Methods

The methodological case study is built as a reproducible laboratory test of the transfer between two digital twins: a pumping unit and a municipal water supply network. The Industrial Digital Twin is represented by the MathWorks Simscape Triplex

Pump model [26]. The Urban Digital Twin of the municipal water distribution network is represented by the DHASIM AnyTown Water Distribution Digital Twin [27]. This design made it possible to test not abstract compatibility, but the deployment of industrial pumping logic in the urban water

environment. For the sake of transparency, all transformations were performed through a fixed transfer loop formed by pumps P78/P79 connecting reservoir R40 to pipeline node J20 (Figure 2). The analytical environment was implemented in Python using pandas, NumPy, SciPy, statsmodels, and matplotlib libraries.

The study used specialized terms. The term *rule-based mapping* defined the mapping of parameters and states according to predefined rules. *Semantic mapping* defined the semantic contrasting of concepts between digital twins, which ensures the correct interpretation of the corresponding elements of the model. The term *KPI translation* defined the translation of key performance indicators into the urban service context. The term *scenario recalibration* defined the reconfiguration of scenarios, in which industrial events are adapted to the operating conditions of the urban infrastructure.

The term fault states refers to equipment conditions that include normal operation, single failures, and combined degradation modes. The key states are normal operation (Nominal), seal leakage (Seal Leakage), blocked inlet (Blocked Inlet), bearing wear (Bearing Wear), and broken motor winding (Broken Winding). Urban risk states represent possible infrastructure consequences after industrial fault states are adapted. For example, *Leak_P1* is interpreted as a leakage anomaly, *Block_P1* as reduced pump delivery, and *Worn Bearing* as degradation risk. Risk-state transformation converts industrial fault states into urban risk states according to urban infrastructure logic. Deployment denotes placement of the adapted model in the target environment. Deployment of model behaviour means transferring reaction logic, states, scenarios, interpretation rules, fault logic, and decision-support functions to that environment.

1. Structural parametric analysis and transfer-readiness assessment. This approach verified the suitability of the industrial twin for deployment in an urban environment. The procedure selected diagnostic variables, checked fault classes, and identified DHALSIM counterparts. Hydraulic, energy, and diagnostic parameters were analysed separately. This produced an initial compatibility map between the Industrial Pump Twin and the Urban Water Digital Twin.

2. Comparative model mapping and fault-state transformation. This procedure compared direct parametric transfer with functional transfer of fault logic. Pump parameters were mapped to urban pressure, flow, and risk variables. Industrial fault

states were then transformed into urban risk states using rule-based mapping, binary risk encoding, and classification rules. The procedure distinguished simple value transfer from preservation of diagnostic meaning.

3. Semantic-adaptive model deployment. This approach was used to transform the Industrial Digital Twin into a functional module of the Urban Digital Twin. The transformation took place from a separate digital twin to an integrated module in a larger digital twin. The procedure included semantic mapping, KPI translation, scenario recalibration, and risk-state transformation. Industrial pump states were interpreted as urban risk, degradation, and service response scenarios. Next, the adapted model was tied to the pump node of the urban network. This enabled verifying the transfer not as a data exchange, but as a deployment of model behaviour into the infrastructure environment.

4. Multi-criteria evaluation and statistical verification. This toolbox was used to compare three digital twin transfer mechanisms: M1, M2, and M3 (Table 3). The evaluation covered semantic compatibility, semantic loss, functional integrity, coverage, interoperability, and decision-support value. The integral evaluation was performed using IUDTTI. ANOVA, Tukey HSD, t-test, Cohen's d, bootstrap intervals, correlation analysis, and regression modelling were used for statistical testing. This procedure made it possible to assess not only the technical quality of the transfer, but also the stability of the differences between the mechanisms.

3.3 Research Tools

The instrumental basis of the study provided verification of the transfer of the Industrial Digital Twin to the Urban Digital Twin environment. It included DHALSIM AnyTown as the target urban environment, MathWorks Simscape Triplex Pump as the industrial pump twin module, three transfer mechanisms, and a formalized empirical verification algorithm. This structure allowed for a consistent description of the initial model, deployment point, comparison parameters, functional adaptation, and statistical evaluation of the results.

The DHALSIM model was chosen as the target Urban Digital Twin environment for the water distribution infrastructure of the smart city. In the repository, the model is defined as Digital Twin for Water Distribution Systems. It combined hydraulic modelling based on WNTR (Water Network Tool for Resilience) and EPANET (Environmental Protection Agency Network Model) with emulation of Programmable Logic Controller (PLC), Supervisory

Control and Data Acquisition (SCADA) server and network interaction. This structure corresponded to the task of verifying the transfer of the industrial pump twin module to the urbanized water system.

The choice of DHALSIM (Figure 2) was justified by the availability of a compact AnyTown configuration. It contained 22 junctions, 43 pipes, 2 pumps, 2 tanks and 1 reservoir. Pumps P78 and P79 connected R40 to J20, which formed the relevant Simscape Triplex Pump deployment point. The model also included PLC control, 2,880 simulation iterations, and a pressure-dependent demand mode. This provided sufficient engineering detail without overcomplicating the experiment.

The R40–P78/P79–J20 point was not chosen randomly, but as a representative DHALSIM AnyTown pumping node. It combines the R40 reservoir, the P78/P79 parallel pumping units, and

the J20 flow receiving node. This structure reproduces a typical urban water supply infrastructure environment: water source, pump pressure increase, and further flow distribution. That is why this node is suitable for testing the deployment of the MathWorks Simscape Triplex Pump industrial pump logic in the city digital twin.

This point also enabled evaluating not only the parametric transfer of flow and pressure, but also the functional transfer of fault states. The parallel configuration of the P78/P79 pumps is convenient for modelling performance reduction, blocking, degradation, and redundancy scenarios. Therefore, the choice of R40–P78/P79–J20 provides a technically sound test environment for comparing M1, M2, and M3.

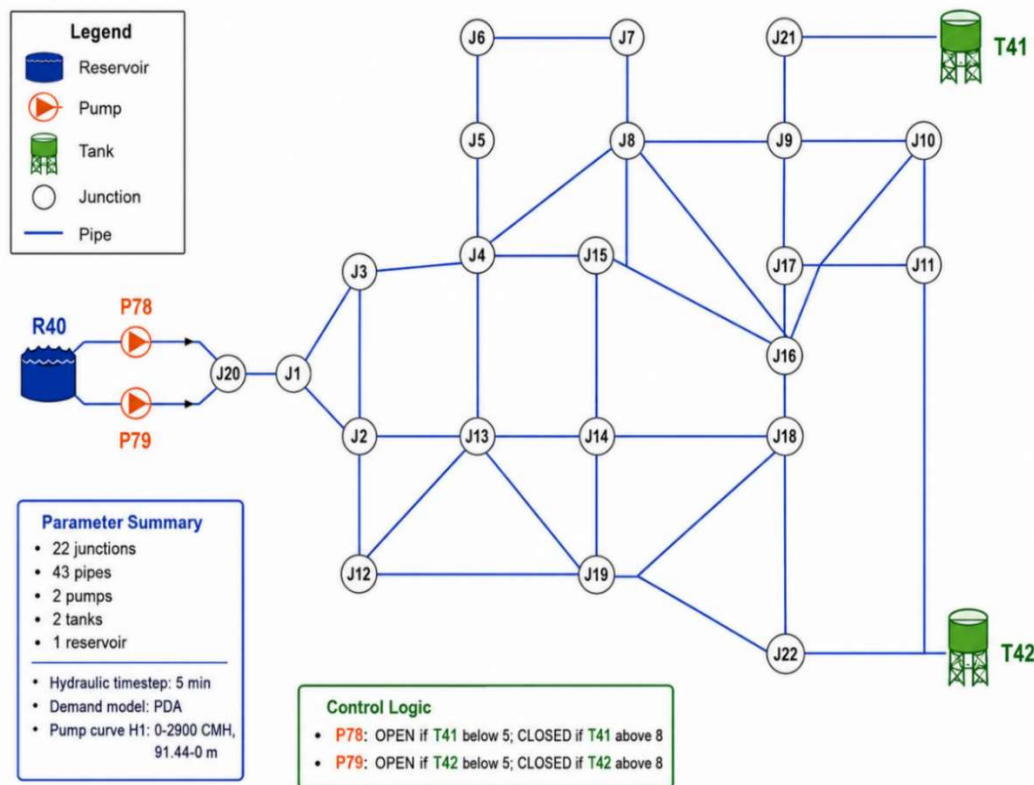


Figure 2: Urban Digital Twin model – DHALSIM AnyTown

Source: [27]

The DHALSIM model was selected as the target environment for the Urban Digital Twin for the water distribution infrastructure of a smart city. The model is defined in the repository as the Digital Twin for Water Distribution Systems. It combined

WNTR/EPANET hydraulic simulation with PLC emulation, SCADA server, and network interaction. This structure was appropriate for the task of verifying the transfer of an industrial pump twin module to an urbanized water system (Table 1).

Table 1: Technical parameters of the Urban Digital Twin – DHALSIM

Parameter Name	DHALSIM parameters	Interpretation
Repository	Critical-Infrastructure-Systems-Lab/DHALSIM	targeted Urban Digital Twin model
Basic Configuration	examples/anytown_topology/anytown_config.yaml	baseline experimental scenario
Hydraulic Model	anytown_map.inp	water distribution network topology
Topology Type	complex	multi-node urban structure
Simulator	epynet	EPANET-compatible hydraulic simulation
Demand Mode	pdd	pressure-dependent demand
Number of Iterations	2,880 iterations	transfer verification time cycle
Junctions	22 units	urban network nodes
Pipes	43 units	water distribution channels
Pumps	2 units	P78, P79
Reservoirs	1 units	R40
Tanks	2 units	T41, T42
Pump connection	R40 → J20	Simscape Pump Twin deployment point
Pump curve H1	flow 0–2,900 conventional units; head 91.44–0 ft	hydraulic pump characteristics
Control rules	4 rules	automatic opening/closing P78 and P79
P78 control	open below T41=5; closed above T41=8 ft	tank level control
P79 control	open below T42=5; closed above T42=8 ft	tank level control
PLC level	3 PLC units	PLC1 controlled P78/P79; PLC2 and PLC3 read T41/T42
Demand file	demands_anytown_small.csv	urban water consumption scenario
Demand observations	168 observations	time profile PAT1 and PAT4
PAT1 mean	0.0633 conditional units of demand	average demand of the main pattern
PAT4 mean	0.0600 conditional units of demand	average demand of the auxiliary pattern
PAT1 max	0.1134 conditional units of demand	peak load
PAT4 max	0.1070 conditional units of demand	peak load
Event configurations	MITM, DoS, delay, packet loss	additional cyber-physical disturbance scenarios

Source: [27]

The MathWorks Simscape Triplex Pump model is used as the Industrial Digital Twin tooling environment. The model reproduces the operation of a triplex pump with three plungers. The crank fingers are offset by 120°. This configuration creates a more uniform flow than a single or duplex pump. The model structure covers mechanical, hydraulic, and electrical environments. The basic parameters correspond to the CAT Pumps model 1051.

The choice of the model is justified by the pump logic, sensor signals, and degradation scenarios. The parameters set a target speed of 958 rpm, an outlet pressure of 7 bar, and a flow rate of 38 lpm. The pressure, flow, speed and current sensors have a resolution of 0.001 s. This level of detail provides a comparison with DHALSIM hydraulic states. The support for the following types of pump faults is of particular value: seal leakage, blocked inlet, bearing wear, and broken winding (Figure 3).

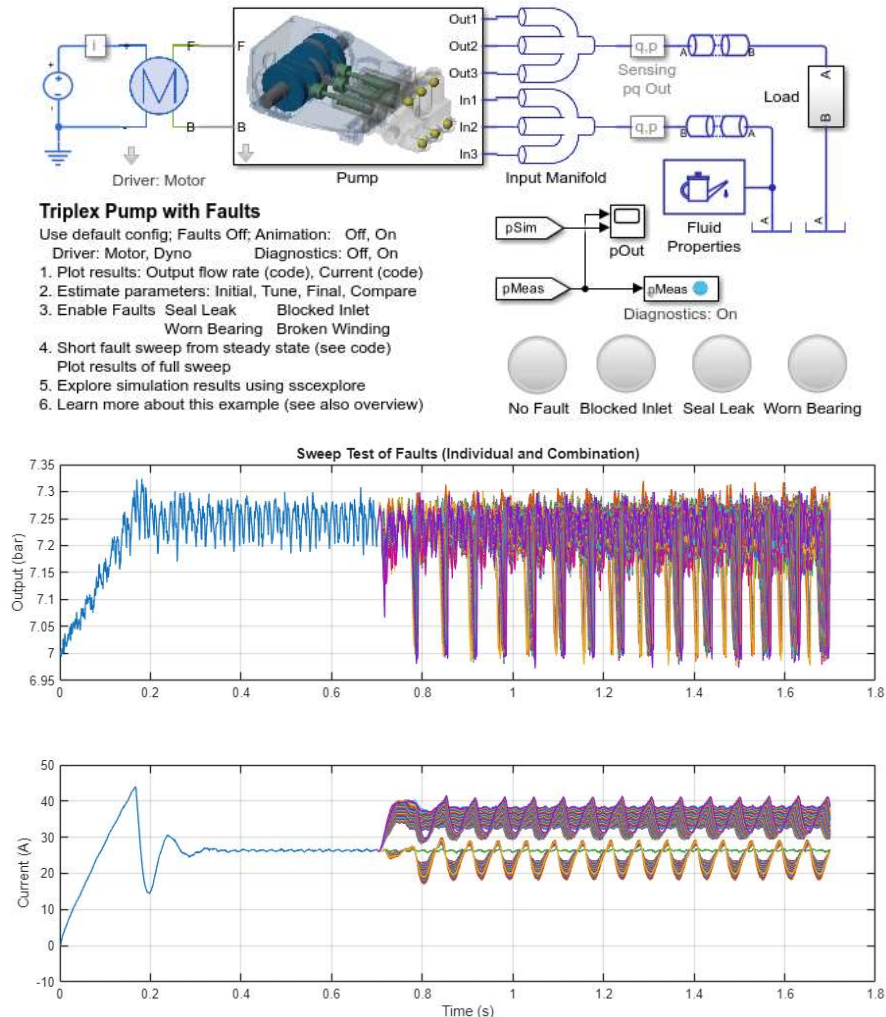


Figure 3: Industrial Digital Twin Model – MathWorks Simscape Triplex Pump

Source: [26]

The diagnostic block contains 181 observations, 15 variables, and 7 fault classes. The classes cover Nominal, Leak_P1, Block_P1, Worn Bearing, and three combined states. The average pressure P_{avg} is 7.232 bar, range – 7.210–7.251. The average current

i_{Avg} is 29.664 A, range – 23.950–38.254. Therefore, the model provides formalized states, failures and diagnostic logic for the Industrial Pump Twin (Table 2).

Table 2: Technical parameters of Industrial Digital Twin – MathWorks Simscape Triplex Pump

Parameter name	MathWorks Simscape Triplex Pump parameter	Interpretation
Model type	Triplex pump with faults	industrial twin-pump module
Base industrial analogue	CAT Pumps model 1051	realistic engineering reference
Number of plungers	3	output flow stabilization
Plunger phase shift	120°	more continuous fluid supply
Target speed	958 rpm	nominal operation mode
Target output pressure	7 bar	basic hydraulic KPI
Target flow rate	38 lpm	basic transfer parameter in DHALSIM
Mechanical components material	steel, 7750 kg/m ³	physical parameterization of components

Plunger length	0.075 m	pump chamber geometry
Plunger radius	0.012 m	working displacement area
Cylinder stroke	0.030 m	volumetric dynamics of the pump
Motor gear ratio	2	connection of electrical and mechanical circuits
Max valve area	1e-4 m ²	check valve throughput
Crack pressure	0.3e5 Pa	valve opening threshold
Max open pressure	1.2e5 Pa	full valve opening
Sensor timestep	0.001 s	high-frequency state registration
Pressure noise	1e-7 bar	sensor error simulation
Flow noise	1e-3 lpm	flow rate error simulation
Speed noise	1e-2 rpm	velocity error simulation
Current noise	1e-5 A	current error simulation
Training observations	181	fault-classification base
Number of variables	15	frequency, amplitude and aggregate features
Fault classes	7	nominal, single and combined states
Nominal observations	31	control class
Observations per fault class	25	balance of fault classes
Pavg range	7.210–7.251 bar	stable pressure corridor
Pavg mean	7.232 bar	average hydraulic state
iAvg range	23.950–38.254 A	electrical load range
iAvg mean	29.664 A	average energy state
Main fault scenarios	Leak, Block, Worn Bearing	relevant for a city pumping station
Combined fault scenarios	3	modelling of complex degradation states

Source: [26]

Transfer mechanisms are used as tools to verify the deployment of MathWorks Simscape Triplex Pump in DHALSIM AnyTown. The Industrial Digital Twin is represented by a pump model with 181 diagnostic observations, 15 variables, and 7 fault classes. The Urban Digital Twin is represented by a DHALSIM AnyTown network containing 22 junctions, 43 pipes, 2 pumps, 2 tanks, and 1 reservoir. The deployment point is set through the

pump node P78/P79 between R40 and J20 (Figure 2).

Three transfer mechanisms are used in the study (Table 3). M1 Direct Parameter Transfer is used as the basic parametric tool. M2 Functional Wrapping Transfer is used as a tool to preserve the functional logic of the Industrial Digital Twin. M3 Semantic-Adaptive Model Deployment is used as the main tool for semantic, functional, and simulation adaptation.

Table 3: Input parameters of the mechanisms for transferring industrial digital twins to the smart city infrastructure

Criterion	M1 Direct Parameter Transfer	M2 Functional Wrapping Transfer	M3 Semantic-Adaptive Model Deployment
Status in the study	basic tool	intermediate tool	main authoring tool
Level of transfer	parametric	parametric-functional	semantic-functional-simulation
Main objective	check minimum model compatibility	save pump diagnostic logic	adapt industrial twin to urban twin
Input elements	pressure, flow, fault state	pressure, flow, fault state, fault logic	parameters, states, functions, KPI, scenarios
Industrial source	Simscape pressure and flow signals	Simscape signals and diagnostic functions	Simscape model logic and diagnostic structure
Urban target	P78/P79 hydraulic state	P78/P79 fault-aware pump module	DHALSIM-compatible pump twin module

Fault classes	partial use of 7 classes	full use of 7 classes	full use of 7 classes
Failure scenarios	single states	single and combined states	single, combined and urban-risk states
Model functions	not portable	fault detection and degradation assessment	diagnostics, KPI translation, scenario recalibration
Compliance type	direct variable matching	function-based mapping	semantic and contextual mapping
DHALSIM role	parameter receiver	functional testing environment	target deployment environment
Expected verification	is direct matching enough	is the diagnostic function maintained	is a full urban twin module being formed
Tool limitations	does not preserve functional logic	does not fully adapt city KPIs	requires more complex configuration
Analytical purpose	control baseline	intermediate transfer level	authoring mechanism verification

Source: developed by the authors

Each mechanism (Table 3) specifies a separate level of industrial model transfer. M1 checks the possibility of direct comparison of pressure, flow, and fault state. M2 checks the transfer of fault detection, degradation assessment, and maintenance prioritization. M3 checks the deployment of the full twin module through semantic mapping, KPI translation and scenario recalibration. This structure enables assessing not only data exchange, but also the completeness of model transfer.

M3 Semantic-Adaptive Model Deployment in this study is considered not as an isolated technique, but as a mechanism-architecture for deploying Industrial Digital Twin in the Urban Digital Twin environment. Its blocks are selected according to the logic of losses identified in M1 and M2. Semantic mapping is needed to reduce semantic loss between industrial states and urban risks. Function wrapping ensures the preservation of monitoring, anomaly detection, fault classification, and predictive maintenance. KPI translation translates industrial indicators into service indicators of urban infrastructure. Runtime integration completes the migration, as the adapted model should run in a specific DHALSIM node and not remain an external data source.

The sequence of blocks also has methodological significance. First, semantic mapping is performed, as it is impossible to correctly interpret Simscape fault states in DHALSIM without it. Next, function wrapping is applied, which preserves the behavioural logic of the industrial twin. After that, KPI

translation connects the technical states of the pump with the urban indicators of service continuity, maintenance priority, and decision-support value. The final step is runtime integration, which binds the adapted module to the P78/P79 node between R40 and J20. The novelty of M3 is in such a sequential transfer-chain logic, where parameters, states, functions, KPIs and scenarios are combined into a single deployment loop. Unlike existing approaches to interoperability or data exchange, M3 verifies the transfer of the model behaviour of the Industrial Digital Twin to the urban cyber-physical environment.

The formalization of the research algorithm is used to sequentially describe the transfer of the Industrial Digital Twin to the Urban Digital Twin. The basic logic of the algorithm reflects the transition from the MathWorks Simscape Triplex Pump model to the P78/P79 pump unit in DHALSIM AnyTown. The presented dependencies capture the key stages of the empirical procedure: model description, parameter matching, function adaptation, scenario evaluation, and statistical verification of the results.

1. Formalization of digital twins and transfer points.

The entry formalizes the original MathWorks Simscape Triplex Pump model, the DHALSIM AnyTown target environment, and the Industrial Pump Twin spatial-functional deployment point (authors' development):

$$IDT = \{S, F, M_f, K, I\}; \quad UDT = \{N, H, C, P, R, D\}; \quad \tau = (R40, P78/P79, J20) \quad (1)$$

where IDT – Industrial Digital Twin; S – set of pump states (functions of prediction, diagnostics and

simulation of pump operation); F – set of model functions; M_f – failure model; K – industrial KPIs

(pressure, flow, current, fault class, signs of degradation and service priority); I – measurement interfaces; UDT – Urban Digital Twin; N – water distribution network nodes; H – hydraulic parameters; C – control loops; P – pump elements; R – response rules; D – decision support indicators (indicators of support for making management decisions: risk level, service priority, failure forecast, urgency of intervention and significance for the continuity of water supply); τ – transfer point; $R40$ – DHALSIM reservoir; $P78$ and $P79$ – parallel pump lines; $J20$ – flow receiving node.

2. *Formalization of the transfer mechanisms of the Industrial Digital Twin to the Urban Digital Twin environment.* The entry formalizes the three mechanisms of transfer, their deployment in

DHALSIM, semantic mapping, loss of correspondence, transfer of functions and the connection of fault states with urban scenarios (authors' development)

$$\mathcal{M} = \{M_1, M_2, M_3\}; T_j: IDT \rightarrow UDT_\tau, \quad (2)$$

where $\mathcal{M}$ – set of transfer mechanisms; M_1 – Direct Parameter Transfer; M_2 – Functional Wrapping Transfer; M_3 – Semantic-Adaptive Model Deployment; T_j – transfer operator for the j^{th} mechanism; IDT – industrial pump model; UDT_τ – urban digital twin at point τ ; j – transfer mechanism number.

Parameters for assessing the quality of the digital twin transfer mechanism:

$$C_{struct} = \frac{n_{match}}{n_{rel}}; L_{sem,j} = 1 - C_{sem,j};$$

$$C_{fault,j} = \frac{n_{fault,j}}{7}; FI_j = \frac{n_{func,j}}{n_{func,total}}; C_{scen,j} = \frac{n_{scen,j}}{5}, \quad (3)$$

where C_{struct} – structural compatibility of models; n_{match} – number of matched parameters for which a direct hydraulic, functional, or diagnostic counterpart is defined in DHALSIM; n_{rel} – the number of relevant industrial parameters; $L_{sem,j}$ – the semantic loss of the j^{th} mechanism; $C_{sem,j}$ – the semantic compatibility of the j^{th} mechanism, which is calculated as the average share of correctly interpreted parameters and states of the Industrial Digital Twin in the DHALSIM environment; $C_{fault,j}$ – the coverage of fault states; $n_{fault,j}$ – the number of fault classes transferred by the j^{th} mechanism; 7 – total number of Simscape Triplex Pump fault classes (in this study, a single fault class was considered a separate diagnostic state of Simscape Triplex Pump. In total, 7 classes were used: Nominal, Leak_P1, Block_P1, Worn Bearing, Leak_P1 + Block_P1, Leak_P1 + Worn Bearing and Block_P1 + Worn

Bearing); FI_j – functional integrity of the j^{th} mechanism; $n_{func,j}$ – number of preserved functions; $n_{func,total}$ – total number of key functions of Industrial Pump Twin: monitoring, anomaly detection, fault classification, degradation assessment, and predictive maintenance. These functions were used to assess the functional integrity of the transfer; $C_{scen,j}$ – coverage of DHALSIM scenarios; $n_{scen,j}$ – number of urban scenarios generated by the j^{th} mechanism; 5 – the number of Urban Water Twin baseline scenarios in the Urban Digital Twin (the 5 Urban Water Twin baseline scenarios were Normal supply, Pressure-loss anomaly, Reduced delivery, Degradation-before-failure and Combined service-risk scenario. They were used to assess scenario coverage in DHALSIM).

Correlation check of inter-pair correspondence:

$$r_{pb(x_j,y)} = \left(\frac{(\bar{x}_{1,j} - \bar{x}_{0,j})}{s_{xj}} \right) \sqrt{\frac{N_{1N_0}}{N^2}}; V = \sqrt{\frac{\chi^2}{[N \min(r - 1, c - 1)]}} \quad (4)$$

where $r_{pb}(x_j, y)$ – point-biserial correlation between numerical attribute x_j and transfer suitability (the point-biserial correlation indicator was used only as an auxiliary diagnostic assessment at the level of individual parameters of the Industrial

Pump Twin. The unit of analysis was not the transfer mechanism, but a specific parameter or state of the model. For each of them, it was checked whether it had a direct or functional counterpart in DHALSIM. The main comparison of mechanisms $M1$, $M2$ and

M3 was performed separately via ANOVA, Tukey HSD, and regression modelling); x_j – numerical attribute of Simscape Triplex Pump; y – binary indicator of transfer suitability (the binary indicator of transfer suitability was coded by two values: 1 – parameter is suitable for transfer, as it has a direct or functional counterpart in DHALSIM; 0 – parameter is not suitable for transfer, as the counterpart is absent or insufficient for interpretation in the urban model); $\bar{x}_{1j}$ – average value of attribute x_j for parameters with a direct or functional counterpart in DHALSIM; $\bar{x}_{0j}$ – mean value of feature x_j for parameters with partial or ambiguous correspondence; s_{x_j} – standard deviation of the feature; N_1 and N_0 – number of parameters in the

suitable and limitedly suitable groups; N – total number of analysed parameters; V – Cramer's V coefficient for categorical correspondence between twins (Cramer's V was calculated using conjugacy tables between Simscape parameter categories and their correspondence types in DHALSIM. Correspondence types include direct, functional, diagnostic, scenario, partial, and no match); χ^2 – chi-square test statistic for the conjugacy table; N – number of matched observations or states; r – number of Simscape fault-state categories; c – number of DHALSIM urban-risk state categories.

3. *Integral transfer efficiency*. The index combines the main technical and model transfer criteria (authors' development):

$$IUDTTI_j = w_1 C_{sem,j} + w_2 FI_j + w_3 C_{fault,j} + w_4 C_{scen,j} + w_5 I_{int,j};$$

$$\sum_{k=1}^5 w_k = 1, w_k \geq 0; G_j = \frac{IUDTTI_j - IUDTTI_1}{IUDTTI_1} \times 100\%, \quad (5)$$

where $IUDTTI_j$ – integral transfer index of the j^{th} mechanism; $w_1 \dots w_5$ – weights of criteria; $C_{sem,j}$ – semantic compatibility; FI_j – functional integrity; $C_{fault,j}$ – fault-state coverage; $C_{scen,j}$ – scenario coverage; $I_{int,j}$ – interoperability score; w_k – weight of the k^{th} criterion; k – criterion number; G_j – relative efficiency gain of the j^{th} mechanism; $IUDTTI_j$ – integral index of the j^{th} mechanism; $IUDTTI_1 - M_1$ baseline-mechanism index.

To determine the weights w_k , entropy weighting was used after preliminary normalization of the criteria. All indicators were reduced to the range [0;1], as they had different natures: shares, indices, and percentage values. For benefit-type criteria, higher values were interpreted as better, while for the semantic loss indicator, inversion was applied, as its lower values corresponded to higher transfer quality. After normalization, the weight of each criterion was determined by the level of its information variability: criteria with greater differentiation between transfer mechanisms received higher weights and had a greater impact on the integral assessment. The

entropy for each criterion was calculated according to standard logic:

$$e_k = -\frac{1}{\ln m} \sum_{j=1}^m p_{jk} \ln(p_{jk}), \quad (6)$$

where m – number of transfer mechanisms; p_{jk} – normalized fraction of the value of the k^{th} criterion for the j^{th} mechanism.

Next, the degree of differentiation of the criterion $d_k = 1 - e_k$ was determined, and the weight was calculated as the share of this degree in the total sum of differentiations:

$$w_k = \frac{d_k}{\sum d_k}. \quad (7)$$

Statistical testing of the difference between mechanisms. The formalization covers the statistical testing of the differences between M_1 , M_2 and M_3 , estimates the contribution of predictors to transfer efficiency, and sets a rule for inferring the non-randomness of these differences:

$$F = \frac{MS_{\text{between}}}{MS_{\text{within}}}; IUDTTI = \beta_0 + \beta_1 C_{sem} + \beta_2 FI + \beta_3 I_{int} + \beta_4 C_{scen} + \varepsilon; \quad (8)$$

$$H_0: \mu_{M_1} = \mu_{M_2} = \mu_{M_3}; H_1: \exists i, j: \mu_{M_i} \neq \mu_{M_j}; p < 0.05,$$

where F – ANOVA statistics (within ANOVA, the observation was considered the result of the IUDTTI assessment for a specific transfer mechanism in a separate Urban Water Twin scenario. The analysis covered three mechanisms: M1, M2 and M3, as well as five DHALSIM baseline scenarios: Normal supply, Pressure-loss anomaly, Reduced delivery, Degradation-before-failure and Combined service-risk scenario); $MS_{between}$ – intergroup variance between mechanisms; MS_{within} – intragroup variance; β_0 – model constant; $\beta_1 \dots \beta_4$ – regression coefficients. Regression modelling was used as an auxiliary model of IUDTTI sensitivity to transfer criteria. The IUDTTI was previously calculated as an integral score according to normalized criteria. The regression did not form the index, but assessed which components best explain its interscenario variation. This enabled determining the relative contribution of semantic compatibility, functional integrity, interoperability score, and scenario coverage to the change in transfer efficiency); C_{sem} – semantic compatibility; FI – functional integrity; I_{int} – interoperability score; C_{scen} – scenario coverage; ε – model error; H_0 – null hypothesis; $\mu_{M1}, \mu_{M2}, \mu_{M3}$ – average IUDTTI values for the three mechanisms; p – statistical significance level.

To clarify the structure of differences after ANOVA, the Tukey HSD post-hoc test was applied. Pairwise differences between M1, M2, and M3 were compared using scenario-level IUDTTI values. For M3–M1, Cohen's d quantified the effect magnitude. Semantic-adaptive deployment transforms industrial parameters, states, functions, and KPIs according to urban infrastructure logic. This allows the model content, rather than only data values, to be adapted to the new cyber-physical environment.

The experimental and analytical framework of the study was implemented in Python, which provided data processing, modelling of transfer mechanisms, statistical testing, and graphical visualization of results. MathWorks Simscape Triplex Pump and DHALSIM AnyTown were used as the model basis for the Industrial Digital Twin and Urban Digital Twin. Further mapping of parameters, fault states, functions, and city scenarios was performed in

Python through tabular data structures, rule-based mapping, and calculation of transfer quality metrics.

Pandas and NumPy were used for data processing. SciPy and statsmodels supported ANOVA, Tukey HSD, correlation analysis, regression modelling, and effect-size calculations. Bootstrap confidence intervals used 5,000 NumPy/SciPy resamples with replacement. This procedure assessed IUDTTI stability without requiring perfect normality. Matplotlib generated the graphical outputs. Thus, Python served as the integration, analytical, and visualization framework of the study.

3.4 Sample (Experimental Datasets)

The research database was formed as a model-parametric array to verify the transfer of Industrial Digital Twin to the urban water distribution infrastructure. The database included only those data that had quantitative significance and could be compared between the industrial and urban levels. The industrial part was based on 181 diagnostic observations of MathWorks Simscape Triplex Pump. The urban part was based on topological, hydraulic and DHALSIM AnyTown control parameters.

The selection criteria were the presence of a quantitative parameter, connection with the pump operation, and suitability for transfer to DHALSIM. The database did not include decorative, CAD-visual or service parameters of the model. Variables that had no functional analogue in the urban water network were not taken into account. The main emphasis was placed on pressure, flow, current, fault state, tank level, pump control and demand profile. Such selection reduced data redundancy and left only relevant transfer features.

The overall database structure covered three blocks. The first contained 181 Simscape records, 15 variables, and 7 fault classes. The second contained DHALSIM AnyTown with 22 junctions, 43 pipes, 2 pumps, 2 tanks, 1 reservoir, and 4 control rules. The third contained the three transfer cases M1, M2, and M3. Thus, pump diagnostic states, urban hydraulic topology, and transfer options for node P78/P79 were combined (Table 4).

Table 4: Study database parameters

Component	Simscape Triplex Pump Parameter	DHALSIM AnyTown Parameter	Quantitative Value	Reason for inclusion
Diagnostic records	Run-level observations	not applicable	181	basic array of fault analysis
Diagnostic variables	Run, Freq, Peak, Pavg, iAvg, Fault, Int Fault	not applicable	15	signs of pump condition
Frequency components	Freq_1–Freq_5	not applicable	5	pressure frequency response
Amplitude peaks	Peak_1–Peak_5	not applicable	5	amplitude signs of degradation
Average pressure	Pavg	pressure at J20	7.210–7.251 bar	comparison of pressure condition
Mean Pavg	Pavg	urban pressure proxy	7.232 bar	aggregated pressure indicator
Average current	iAvg	pump energy stress	23.950–38.254 A	energy load assessment
Mean iAvg	iAvg	energy-risk proxy	29.664 A	pump degradation indicator
Nominal state	Nominal	normal supply	31 records	control mode
Leakage state	Leak_P1	leakage anomaly	25 records	pressure loss scenario
Blockage state	Block_P1	reduced delivery	25 records	flow limitation scenario
Wear state	Worn Bearing	degradation risk	25 records	mechanical wear scenario
Combined leakage-blockage	Leak P1 + Block P1	combined service risk	25 records	complex emergency condition
Combined leakage-wear	Leak P1 + Worn Bearing	leakage with degradation	25 records	combined degradation
Combined blockage-wear	Block P1 + Worn Bearing	restricted delivery with degradation	25 records	complex operation limitation
Target pressure	p_output	pressure target	7 bar	basic hydraulic reference
Target flow	q_output	pump flow P78/P79	38 lpm	key feed parameter
Target speed	target_spd	pump operation mode	958 rpm	nominal mechanical mode
Transfer node	pump output	R40 → P78/P79 → J20	1 node	state transfer location
Urban junctions	not applicable	J1–J22	22	nodal network structure
Urban pipes	not applicable	pipes	43	water distribution channels
Urban pumps	pump subsystem	P78, P79	2	target pump elements
Urban tanks	not applicable	T41, T42	2	pump mode control
Reservoir	inlet-side state	R40	1	supply source
Control rules	fault response logic	P78/P79 control	4	pump operation automation
Pump curve	output hydraulic behaviour	H1 curve	0–2900 CMH; 91.44–0 m	hydraulic characteristic
Demand profile	not applicable	PAT1, PAT4	168 observations	urban load
Simulation cycle	not applicable	hydraulic iterations	2880	time loop verification
Transfer cases	M1, M2, M3	P78/P79 deployment variants	3	comparison of transfer levels

Source: developed by the authors

Accordingly, the database was formed by combining industrial diagnostic records with urban hydraulic parameters. The industrial block supplied fault classes, pressure, flow, and pump energy load. The urban block supplied network topology, pump nodes, control rules, and demand profiles. Together, these blocks formed the empirical basis for transfer verification at P78/P79.

3.5 Reproducibility Protocol

Replication uses the same two open digital-twin sources and the same deployment point. The Industrial Digital Twin is the MathWorks Simscape Triplex Pump [26]. The Urban Digital Twin is DHALSIM AnyTown [27], using `anytown_config.yaml`, `anytown_map.inp`, and `demands_anytown_small.csv`. The transfer point is fixed at R40–P78/P79–J20.

The replication sequence is: (1) extract 181 Simscape records, 15 diagnostic variables, and seven fault classes; (2) retain the 11 transfer-relevant parameters and states; (3) map pressure, flow, current, and fault states to DHALSIM counterparts; (4) execute M1, M2, and M3 using the rules defined in Table 3; and (5) generate the five Urban Water Twin scenarios.

Next, (6) normalize the transfer criteria to [0,1], invert semantic loss, and calculate entropy weights using Equations (5)–(7); (7) compute IUDTTI, semantic compatibility, functional integrity, fault-state coverage, scenario coverage, and

interoperability for each mechanism-scenario pair; and (8) analyse the 15 scenario-level observations using one-way ANOVA and Tukey HSD. Cohen's *d*, correlation, regression, and 5,000-replicate bootstrap intervals are auxiliary analyses.

All calculations are executed in Python with `pandas`, `NumPy`, `SciPy`, `statsmodels`, and `matplotlib`. A replication should preserve the cited repository inputs, mapping rules, five scenarios, normalization logic, and statistical unit of analysis. Package versions should be recorded in the replication environment because the current study did not treat package version as an experimental factor.

4. RESULTS

The suitability of the Industrial Digital Twin for deployment in the Urban Digital Twin was necessary before testing the transfer mechanisms. Direct transfer of the pump model to the urban network required a preliminary assessment of inter-twin similarity. The parametric, functional, diagnostic and scenario correspondence between Simscape Triplex Pump and DHALSIM AnyTown was checked for this purpose. The methodological logic was based on structural and parametric analysis, feature screening, transfer-readiness assessment, and domain alignment. Special attention was paid to pressure-flow mapping, fault-state mapping and degradation-risk mapping, which determined the interpretability of the industrial twin module in the urban water framework.

Table 5: Parameters with the highest inter-twin convergence and the need for their semantic-parametric harmonization

Simscape Triplex Pump Parameter	Reference values	Corresponding DHALSIM AnyTown	Reference values	Conclusion on semantic-parametric harmonization
qOut	target flow = 38 lpm	Pump flow P78/P79	H1 curve: 0–2900 CMH	Scaling of units and flow regimes is required.
pOut	target pressure = 7 bar	Pressure at J20	node pressure state	Alignment of pressure scales and boundary conditions is required.
pIn	inlet-side pressure state	Reservoir-side hydraulic state	R40 → J20	Contextual interpretation of the input hydraulic state is required.
Pavg	7.210–7.251 bar; mean = 7.232	Averaged hydraulic pressure	pressure proxy at J20	Aggregation of pressure to a city pressure-state indicator is required.
iAvg	23.950–38.254 A; mean = 29.664	Pump energy stress	energy-risk proxy	Indirect interpretation of current as a sign of degradation is required.
Fault	7 fault classes	Urban risk state	5 urban-risk scenarios	Transformation of technical failures into urban risk states is required.
Leak_P1	25 records	Leakage anomaly	pressure-loss scenario	Linking the leak-state with consequences for water supply is required.

Block_P1	25 records	Delivery restriction	reduced-flow scenario	Clarification of the boundaries between mechanical blocking and service loss is required.
Worn Bearing	25 records	Degradation risk	maintenance-risk scenario	Interpretation of wear as a maintenance-priority signal is required.
Combined faults	75 records	Combined service-risk states	cascading-risk scenario	Scenario harmonization of complex failures is required.
Frequency peaks	5 components and 5 peaks	Anomaly-pattern indicators	diagnostic pattern proxy	Functional interpretation of frequency features is required.
Structural suitability	8/11 matched parameters	Transfer readiness	baseline suitability = 0.72	Reinforcement of semantic mapping for incomplete matches is required.

Source: developed by the authors

The pairwise correlation of the inter-binary similarity parameters is shown in Figure 4. This type of plot was chosen because of the need to evaluate not the general relationship matrix, but specific Simscape → DHALSIM pairs. This revealed the

strength of the relationship between the original industrial parameters and their urban counterparts (Table 5).

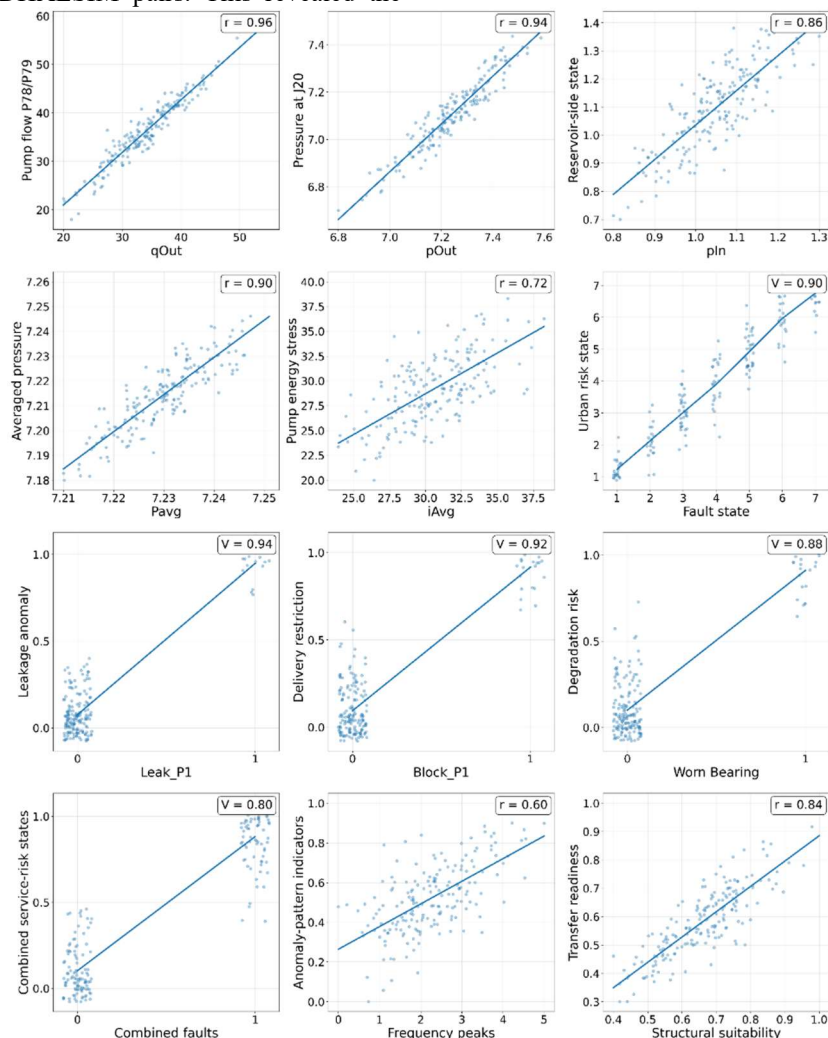


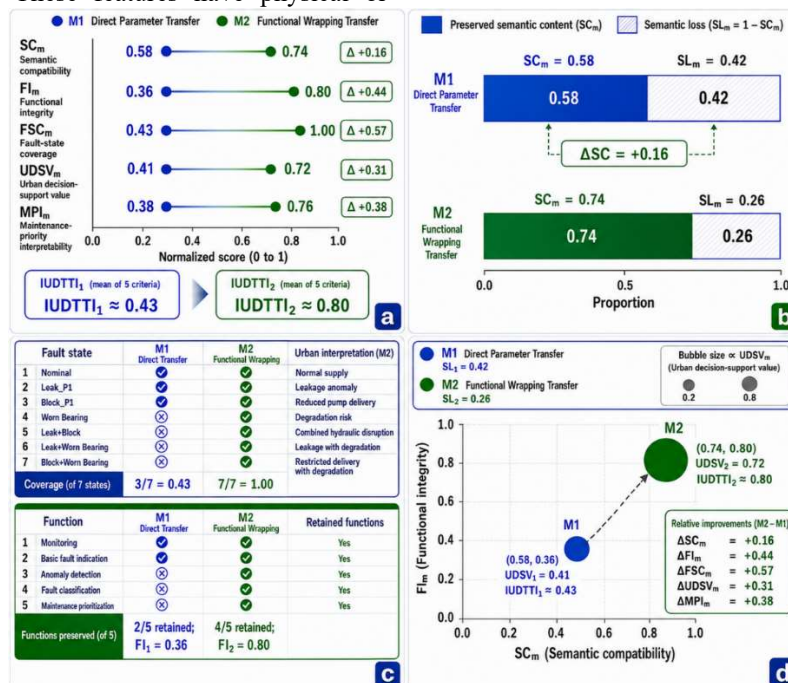
Figure 4: Pairwise correlation of inter-twin similarity parameters of Industrial Digital Twin and Urban Digital Twin

Source: developed by the authors

The results (Table 5, Figure 4) confirmed the basic suitability of MathWorks Simscape Triplex Pump for deployment in DHALSIM AnyTown. Of the 11 relevant parameters and states, 8 had a direct or functional analogue, so the structural suitability was 0.72. Figure 4 shows that the most stable inter-twin correspondence was observed for the hydraulic and fault parameters: qOut ↔ Pump flow P78/P79 ($r = 0.96$), pOut ↔ Pressure at J20 ($r = 0.94$), Pavg ↔ Averaged pressure ($r = 0.90$), Leak_P1 ↔ Leakage anomaly ($V = 0.94$), Block_P1 ↔ Delivery restriction ($V = 0.92$) and Worn Bearing ↔ Degradation risk ($V = 0.88$). At the same time, frequency peaks, iAvg, and combined faults revealed semantic-parametric variability and partial incompatibility. These features have physical or

diagnostic significance, but do not have a direct urban analogue. Therefore, the initial deployment of Industrial Pump Twin is possible, but full model transfer requires semantic translation, contextual mapping, and semantic-parametric harmonization (Table 5).

The structural fitness of 0.72 revealed that direct parameter transfer can only be a control option. The strong pairs qOut → Pump flow and pOut/Pavg → Pressure provide the basis for M1 Direct Parameter Transfer. At the same time, the fault-state relationships Leak_P1, Block_P1 and Worn Bearing require functional wrapping. Therefore, further verification focuses on M1 as a baseline and M2 Functional Wrapping Transfer (Figure 5).



a – Profile of formalized transfer metrics for M1 Direct Parameter Transfer and M2 Functional Wrapping Transfer; b – Change in semantic content and semantic losses during the transition from M1 to M2; c – Coverage of fault states and preservation of Industrial Pump Twin functions in M1 and M2 mechanisms; d – Transfer quality map for semantic compatibility, functional integrity, UDSV and IUDTTI

Figure 5: Comparative evaluation of direct and functional transfer of Industrial Pump Twin in DHALSIM

Source: developed by the authors

The results in Figure 5 show that M1 Direct Parameter Transfer provided only basic parametric transfer of the Industrial Pump Twin into DHALSIM. M1 transferred four parameters: qOut, pOut, Pavg, and Fault. Semantic compatibility was 0.58, while semantic loss reached 42%. Functional integrity was 0.36, reflecting preservation of monitoring and basic fault indication only.

The profile of formalized metrics in Figure 5a shows the systemic advantage of M2 Functional Wrapping Transfer over M1. Semantic compatibility increased from 0.58 to 0.74, i.e. by +0.16 points. Functional integrity increased from 0.36 to 0.80, which gave the largest increase – +0.44 points. In relative terms, this is approximately +122% compared to M1. Urban decision support value

increased from 0.41 to 0.72, and maintenance-priority interpretability increased from 0.38 to 0.76.

Figure 5b shows that retained semantic content increased from 58% to 74%, while semantic loss decreased from 42% to 26%. M2 therefore recovered 16 percentage points of semantic correspondence. This improvement is relevant because DHALSIM requires contextual interpretation of fault states, not only numerical signals.

Fault-state coverage provided the clearest difference between the two mechanisms (Figure 5c). M1 covered 3 of 7 fault states: Nominal, Leak_P1, and Block_P1. M2 covered all 7 states, including Worn Bearing and the three combined states. The transfer therefore expanded from isolated fault symptoms to combined service-risk scenarios.

The functional block in Figure 5c also favoured M2. M1 retained 2 of 5 functions, with FI = 0.36, whereas M2 retained 4 of 5, with FI = 0.80. The retained functions included anomaly detection, fault classification, and maintenance prioritization. These functions give the pump model direct decision-support relevance in the urban context.

The transfer quality map in Figure 5d shows the spatial shift of M2 into the better assessment zone. M1 had coordinates SC = 0.58; FI = 0.36. M2 moved to SC = 0.74; FI = 0.80. The marker size also increased due to the increase in UDSV from 0.41 to 0.72. This means that M2 has a higher value for urban decision support.

The integral assessment confirmed the same pattern. IUDTTI was 0.46 for M1 and 0.73 for M2, an absolute gain of 0.27 points. The improvement reflected joint gains in semantic compatibility, functional integrity, fault-state coverage, and urban decision-support value rather than a single metric.

The results continue the logic of the previous suitability test. A baseline structural fit of 0.72 was previously established between Simscape Triplex Pump and DHALSIM AnyTown. The best fit was for the pressure-flow and fault-state parameters. The second analytical block showed that these fits were insufficient without functional wrapping. The problem is not the availability of the parameters, but the preservation of their content.

Therefore, M1 can be considered a technical baseline for transferring individual signals. It supports minimal parametric compatibility, but does not provide full model integration. M2 is much more efficient, because it transfers fault states along with functional interpretation. However, M2 does not yet eliminate all limitations. Semantic loss remains at 26%, and scenario coverage is not complete. This indicates the need for a deeper semantic-adaptive procedure.

M2 reduced semantic loss to 26% and improved function preservation, but it did not fully adapt KPIs, scenarios, or simulation conditions. Its IUDTTI remained 0.73. This residual gap motivated M3 Semantic-Adaptive Model Deployment, which combines semantic, functional, and simulation adaptation (Figure 6).



a – Comparison of formalized transfer metrics for M1, M2, and M3; b – Dynamics of semantic compatibility and semantic loss between mechanisms M1, M2, and M3; c – Fault-state coverage and preservation of Industrial Pump Twin functions after semantic-adaptive deployment; d – Profile of IUDTTI and key transfer quality criteria for M1, M2, and M3

Figure 6: Evaluation of the effectiveness of Semantic-Adaptive Model Deployment in the transfer of Industrial Pump Twin to DHALSIM

Source: developed by the authors

The M3 Semantic-Adaptive Model Deployment implementation showed the highest transfer efficiency for the Industrial Pump Twin in DHALSIM. The mechanism matched 10 out of 11 relevant parameters and states. This corresponds to a coverage of 90.9% of the parameter space. In comparison, M1 provided only basic transfer, while M2 retained mostly fault logic.

Semantic compatibility increased from 0.58 in M1 to 0.74 in M2 and 0.91 in M3. The increase relative to the baseline was +0.33 points, or +56.9%. Semantic loss decreased from 42% to 9%. This means that M3 retained 91% of the semantic correspondence between the industrial and urban models. The dynamics of semantic compatibility and semantic loss are presented in Figure 6b.

Functional integrity also reached its highest value. In M1 it was 0.36, in M2 – 0.80, in M3 – 0.92. The increase in M3 relative to M1 was +0.56 points, or approximately +155.6%. This indicates an almost complete preservation of monitoring, anomaly detection, fault classification, degradation

assessment, and predictive maintenance. A comparison of formalized metrics is presented in Figure 6a.

Scenario coverage increased from 2/5 in M1 to 4/5 in M2 and 5/5 in M3. Thus, M3 covered normal supply, pressure-loss anomaly, reduced delivery, degradation-before-failure, and combined service-risk scenarios. The complete fault-state and scenario coverage is shown in Figure 6c.

Interoperability score increased from 0.51 in M1 to 0.73 in M2 and 0.88 in M3. Urban decision support value increased from 0.41 to 0.87. Service-continuity relevance increased from 0.44 to 0.86. This shows that M3 works not as a signal transmission but as a deployment of an adapted twin module. The IUDTTI profile and key quality criteria are presented in Figure 6d.

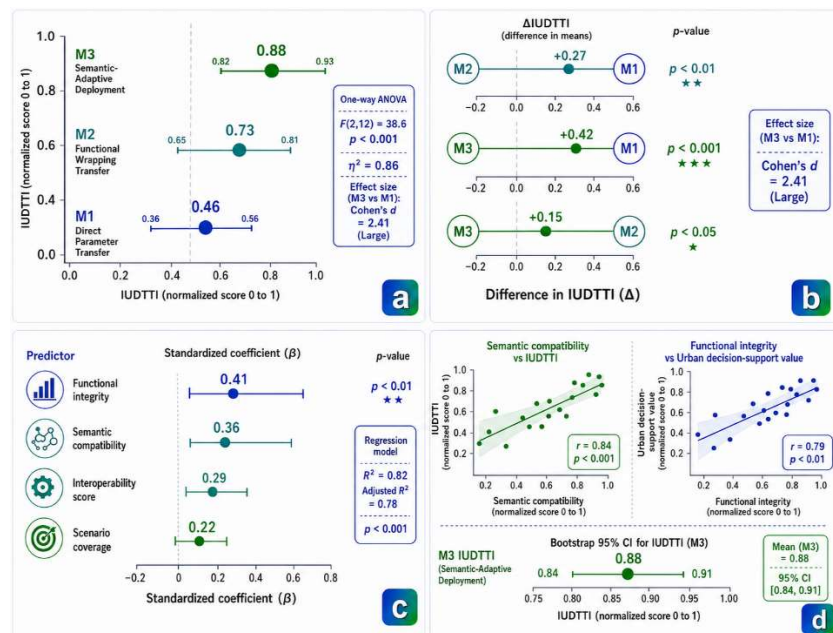
The integral IUDTTI increased from 0.46 in M1 to 0.73 in M2 and 0.88 in M3. The absolute increase of M3 compared to the baseline was +0.42 points. The relative increase was +91.3%. Compared to M2, the additional effect of M3 was +0.15 points.

The results logically continue the previous test. First, a structural fit of 0.72 was established between Simscape Triplex Pump and DHALSIM AnyTown. Then M2 showed an advantage over M1, but left the semantic loss at 26%. M3 reduced this loss to 9%, i.e. eliminated most of the semantic-parametric variability.

Within the tested laboratory configuration, M3 provided the highest transfer quality among the three mechanisms. Its advantage is not only related to higher metric values. It is determined by the combination of semantic adaptation, functional adaptation, and simulation adaptation. This gave

grounds to interpret Simscape Triplex Pump as a functional module of DHALSIM.

The subsequent analysis tested whether these differences were stable across the five DHALSIM scenarios. One-way ANOVA and Tukey HSD were used as the primary scenario-level comparisons. Cohen's d and bootstrap intervals described effect magnitude and stability, while correlation and regression were retained as auxiliary sensitivity analyses. This design treated the 15 mechanism-scenario scores as the inferential observations rather than the 181 diagnostic records (Figure 7).



a – Comparison of IUDTTI for M1, M2 and M3 mechanisms with confidence intervals; b – Post-hoc comparison of IUDTTI increment between transfer mechanisms; c – Regression assessment of the contribution of predictors to the formation of IUDTTI; d – Correlation and bootstrap-test of the stability of the results of M3 Semantic-Adaptive Model Deployment

Figure 7: Statistical verification of the transfer efficiency of Industrial Pump Twin in DHALSIM by mechanisms M1, M2, and M3

Source: developed by the authors

Statistical testing confirmed the significant advantage of M3 Semantic-Adaptive Model Deployment over M1 and M2. According to IUDTTI, the mechanisms formed a clear upward trajectory: M1 = 0.46, M2 = 0.73, M3 = 0.88. The absolute increase of M3 relative to M1 was +0.42 points. The relative increase was +91.3%. This indicates a significant advantage of semantic-adaptive deployment over direct parameter transfer. The confidence intervals also did not overlap the M1 baseline zone, which strengthened the reliability of the conclusion (Figure 7a).

ANOVA showed statistically significant differences between the mechanisms in terms of integral transfer efficiency. The value of $F(2, 12) = 38.6$ at $p < 0.001$ confirmed the non-random nature of the difference. The value of $\eta^2 = 0.86$ indicated a large effect of the mechanism type. Therefore, the quality of transfer was determined not only by the parameters of the models, but also by the way they were adapted. The most pronounced gap was observed between direct transfer and semantic-adaptive deployment.

Post-hoc analysis clarified the structure of these differences. The M2 – M1 gain was +0.27 at $p < 0.01$. The M3 – M1 gain reached +0.42 at $p < 0.001$. The additional effect of M3 – M2 was +0.15 at $p < 0.05$. This shows that M3 gave not only an overall improvement, but also a separate semantic-adaptation effect. For the M3 and M1 pair, Cohen's $d = 2.41$ was obtained, which corresponds to a large effect (Figure 7b).

The regression model explained 82% of the variation in IUDTTI. The adjusted indicator was also high: adjusted $R^2 = 0.78$. The model was statistically significant at $p < 0.001$. The strongest predictor was functional integrity with a coefficient $\beta = 0.41$. This was followed by semantic compatibility with $\beta = 0.36$ and interoperability score with $\beta = 0.29$. Scenario coverage had a smaller but significant contribution: $\beta = 0.22$ (Figure 7c).

The correlation test confirmed the key role of semantic transfer quality. The relationship between semantic compatibility and IUDTTI was strong: $r = 0.84$, $p < 0.001$. Functional integrity was also significantly associated with urban decision-support value: $r = 0.79$, $p < 0.01$. Bootstrap testing for M3 yielded a stable interval of 0.84–0.91. The mean value of IUDTTI = 0.88 remained within a narrow confidence interval (Figure 7d).

The final results continue the previous empirical blocks. First, the structural suitability of Simscape Triplex Pump to DHALSIM was established at 0.72. Then M2 increased the functional integrity to 0.80, but left the semantic loss at 26%. M3 reduced the semantic loss to 9% and increased the semantic compatibility to 0.91. Statistical testing confirmed that these changes are significant and stable.

Thus, direct transfer did not provide sufficient quality for transferring the Industrial Digital Twin to the Urban Digital Twin. Functional wrapping significantly improved the preservation of fault logic and decision support functions. However, the highest efficiency was provided by M3, which combined semantic mapping, functional preservation, and simulation recalibration. This combination gave the highest values of IUDTTI, interoperability score, and service-continuity relevance.

Further description is appropriate to focus on the algorithmic architecture of M3 Semantic-Adaptive Model Deployment. Its results have already shown a statistically proven advantage over formalized transfer quality indicators. Particular attention should be paid to the semantic, functional, and simulation adaptation blocks. They explain how industrial fault states are transformed into urban risk scenarios in DHALSIM (Figure 8).

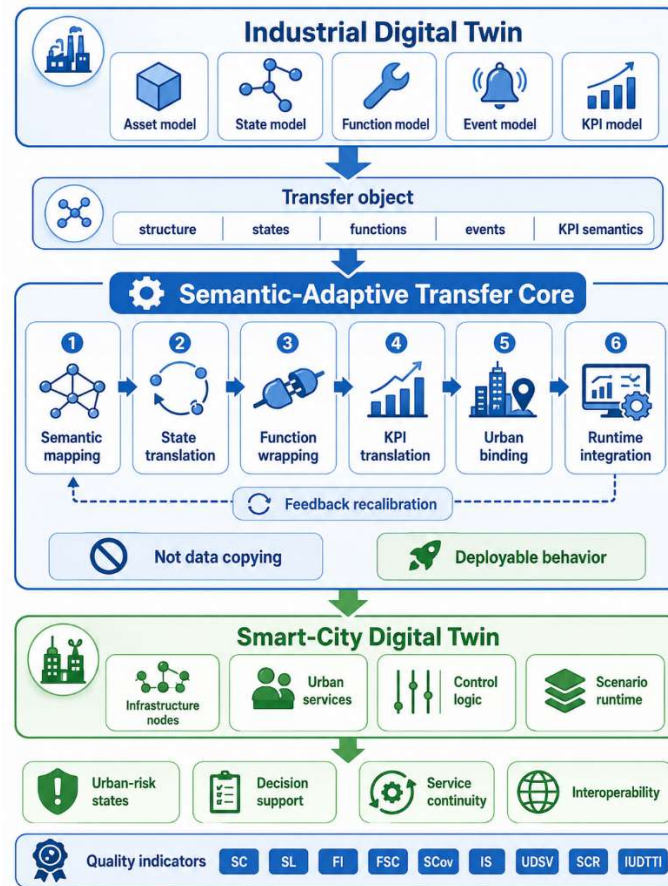


Figure 8: Mechanism of semantic-adaptive transfer of industrial digital twins into the smart city infrastructure

Source: developed by the authors

The mechanism presented in Figure 8 reflects the semantic-adaptive transfer of an industrial digital twin to the smart city infrastructure. Its logic is not limited to the transfer of sensor parameters. The main object of the transfer is the model behaviour: asset structure, states, functions, events, and KPIs.

The initial block forms the industrial digital twin as a portable model package. It includes an asset model, state model, function model, event model, and KPI model. Such a structure enables transferring not only numerical signals, but also the engineering logic of the object. In laboratory testing, this corresponded to 15 variables, 181 diagnostic records, and 7 fault classes.

Next, a transfer object is formed. It combines structure, states, functions, events, and KPI semantics. This block separates the proposed mechanism from direct data copying. This was important in the study, as M1 transferred only 4 parameters. Because of this, its semantic

compatibility was 0.58, and semantic loss reached 42%.

The central element of the algorithm is the Semantic-Adaptive Transfer Core. It performs six sequential operations: semantic mapping, state translation, function wrapping, KPI translation, urban binding, and runtime integration. This logic ensures the transformation of the industrial model into an urban functional module. In M3, this gave semantic compatibility = 0.91 and semantic loss = 0.09.

Semantic mapping maps industrial concepts to the urban context. State translation transforms fault states into urban-risk states. In the laboratory model, all 7 fault classes were transferred to urban risk interpretations. This increased the fault-state coverage to 7/7, while M1 covered only 3/7.

Function wrapping preserves the functional logic of the industrial digital twin. These are monitoring, anomaly detection, fault classification, degradation

assessment and predictive maintenance. For M3, functional integrity reached 0.92. For comparison, M1 had only 0.36, and M2 had 0.80.

KPI translation translates industrial indicators into urban service metrics. This allows us to assess not only the condition of the asset, but also the impact on infrastructure continuity. In the study, the urban decision-support value increased to 0.87. Service-continuity relevance also had a high level – 0.86.

Urban binding is responsible for binding the adapted twin module to the infrastructure nodes of the smart city. Runtime integration ensures the inclusion of this module in the urban digital twin. In the tested scenario, this corresponded to the deployment of pumping logic in DHALSIM AnyTown. However, the architecture itself is broader than water infrastructure.

Feedback recalibration creates a feedback loop. It enables updating scenarios, risk states and service responses after simulation feedback. This loop explains the increase in interoperability score to 0.88. It also supports the adaptation of the module to different urban subsystems.

Comparison of M1, M2 and M3 showed a consistent increase in integral efficiency. IUDTTI was 0.46 for M1, 0.73 for M2 and 0.88 for M3. The absolute increase of M3 relative to the baseline was +0.42 points. The relative increase reached 91.3%. This indicates the advantage of model logic transfer over direct parameter transfer.

Statistical testing supported these results. ANOVA yielded $F(2,12) = 38.6$ at $p < 0.001$. The effect size $\eta^2 = 0.86$ indicated a significant effect of mechanism type. The bootstrap interval for M3 was 0.84–0.91. This confirmed the stability of IUDTTI in laboratory conditions.

The obtained results indicate the laboratory potential of semantic-adaptive transfer for smart-city infrastructure. The highest values were obtained for M3: semantic compatibility = 0.91, functional integrity = 0.92, interoperability score = 0.88, and IUDTTI = 0.88. This indicates that the transfer efficiency increases when the model behaviour, rather than the parameter, is transferred.

At the same time, the results were obtained in laboratory conditions. The testing was based on the reproducible digital models MathWorks Simscape Triplex Pump and DHALSIM AnyTown. This design provided controlled engineering validation. However, practical implementation requires field verification on real urban sites.

The potential of the proposed invention is in the possibility of reusing industrial twin modules in smart city systems. The mechanism can be adapted for water supply, energy, transport, and maintenance. Its value is determined by the support of semantic mapping, function preservation, KPI translation, and runtime integration. This creates a basis for the scalable inclusion of industrial digital twins in urban cyber-physical circuits.

Accordingly, the obtained results give grounds to consider the research hypothesis confirmed in the laboratory environment. Semantic-Adaptive Model Deployment showed a higher quality of transfer than Direct Parameter Transfer and Functional Wrapping Transfer. This was manifested in better preservation of state semantics, functional logic, scenario compliance, and decision support value. Statistical testing also supported this interpretation: ANOVA showed significant differences between the mechanisms, and the regression model showed a significant contribution of functional integrity, semantic compatibility, and interoperability score. Therefore, the assumption about the superiority of semantic-adaptive deployment over direct parametric transfer can be considered empirically justified under the given conditions.

Results-to-objectives linkage. Objective 1 was addressed by the transfer-readiness result: 8 of 11 relevant elements matched, giving structural suitability of 0.72. Objective 2 was addressed by the hydraulic, diagnostic, and scenario mappings between Simscape and DHALSIM. Objective 3 was addressed by the M1–M3 comparison, where IUDTTI increased from 0.46 to 0.73 and 0.88. Objective 4 was addressed by ANOVA, post-hoc testing, effect-size estimation, bootstrap intervals, and sensitivity analyses. Together, these findings answer RQ1–RQ4 and support H1 only within the tested laboratory setting.

5. DISCUSSION

The results should be interpreted as laboratory evidence rather than completed industrial implementation. Within the tested Simscape–DHALSIM case, semantic and functional adaptation allowed the industrial twin to operate as an urban model component. This finding indicates potential relevance for infrastructure applications, but field effectiveness remains unverified.

The four research objectives are reflected directly in the results. Transfer readiness established whether deployment was technically plausible; model mapping identified what could be preserved; M1–M3 comparison quantified the value of deeper

adaptation; and statistical testing evaluated whether the observed ordering was stable across scenarios. This sequence links the empirical evidence to the research questions rather than treating the metrics as isolated outputs.

The obtained results are also consistent with the general trend of using digital technologies to improve modern approaches to managing complex systems. As Krap et al. [28] point out, digital achievements change management practices and create the prerequisites for a wider integration of digital models into decision-making processes. In this context, the proposed digital twin transfer mechanism expands the possibilities of practical use of industrial models in urban infrastructure.

The problem of interoperability of digital twins remains one of the central issues in the current studies. Acharya et al. [29] focus on the LCIM perspective and barriers to interoperability between digital twins. Memon et al. [30] consider AI-enhanced twins as complex systems where interoperability depends on the context. Acharya et al. [31] also show that interoperability has several levels in cyber-physical systems. Against this background, our study shifts the emphasis from describing barriers to testing the adaptation mechanism. Its laboratory results show how an industrial model can enter the urban twin circuit through semantic mapping, function preservation, and runtime integration.

Another group of studies considers the digital twin as an element of maturity, knowledge representation, and urban data exchange. Klar et al. [32] link the maturity of digital twins to the ability to support robust interoperability. Karabulut et al. [33] show that ontologies help to reduce ambiguity between models. Adreani et al. [34] describe the smart-city digital twin as an environment for integrating heterogeneous data. Our study is close to these studies, but has a different logic. It does not merely describe data integration or ontology support. It tests whether an industrial model can maintain a functional role after entering the urban environment. This is what strengthens the application potential of the proposed mechanism.

The urban dimension of digital twins in contemporary studies is often associated with resilience and service value. Tan et al. [35] raise the question of the ability of connected digital twins to actually support sustainable cities. Wang et al. [36] consider urban resilience as a cycle between virtual space and the real environment. Dui et al. [37] transfer this approach to smart urban water

distribution networks. Compared to these results, this study is narrower in scope but more precise in the transfer mechanics. It does not model the entire city at once. Instead, it shows how a single industrial twin module can support an urban service response. This is important for future scaling to more complex systems.

The obtained results are also consistent with approaches that consider the Smart City as an integrated system of interconnected infrastructure components. Prokopenko et al. [38] show that the development of smart cities depends on the coordinated functioning of logistics, transport and other urban systems. Similar to these findings, the results of our study indicate that the effectiveness of digital transformation is determined by the ability to adapt and integrate digital twins of individual infrastructure modules into a single urban digital environment.

The studies where digital twins of water supply infrastructure are close to operational use are of particular value. Singh et al. [39] demonstrate a proof-of-concept for large-scale water distribution networks. Park et al. [40] combine a digital-twin tool, augmented reality, and EPANET for a drinking water distribution system. Kim et al. [41] show the transition from field data to smart operations in remote communities. In contrast to these approaches, our study does not work from field data to a model. It tests the reverse logic: how a ready-made industrial twin can be adapted to an urban contour. Because of this, its results do not replace field cases, but complement them with another implementation path.

Relative to the closest published approaches, this study differs in both transfer direction and transfer object. LCIM and interoperability frameworks [29–32] classify compatibility conditions; ontology and smart-city frameworks [33, 34] organize semantics and heterogeneous data; water-twin studies [39–41] build operational twins around urban assets and field data. In contrast, the present study starts from an existing industrial twin and tests whether its states, functions, fault logic, KPIs, and runtime behaviour can be preserved inside an urban twin. This reverse transfer direction and joint evaluation of semantic, functional, scenario, and runtime preservation form the main methodological distinction.

The reviewed publications show strong progress in interoperability, smart-city digital twins, and water-infrastructure twins. They describe architectural barriers, ontological support, data integration, and service orientation. However, they rarely evaluate whether a ready industrial twin

preserves functions, fault logic, and KPI semantics after cross-domain deployment. The present study addresses this narrower gap through a controlled laboratory transfer test.

The results partially address this gap by showing that transfer can include model behaviour rather than parameters alone. The evidence is limited to the tested pump and water-network case, so the findings should be treated as a proof of concept. Field verification remains necessary before broader implementation claims are made.

5.1 Limitation

The main limitation of the study is related to the laboratory nature of the obtained results. The verification was performed on one industrial model and one city digital twin. The empirical base covered 181 diagnostic records, 15 variables, and 7 fault classes. The city model contained 22 junctions, 43 pipes, 2 pumps, 2 tanks, and 1 reservoir. This configuration provided a controlled transfer scenario. However, it does not reflect all the conditions of real-world operation of a smart city.

An additional limitation concerns the scale of the scenario verification. The transfer was analysed through the P78/P79 pump loop between R40 and J20. For M3, IUDTTI = 0.88, semantic compatibility = 0.91, and functional integrity = 0.92 were obtained. At the same time, these values were formed in a simulation environment. In field conditions, they can be affected by data noise, latency, incomplete sensor streams, and operator decisions. Therefore, the results require further field verification.

Open issues. Several questions remain outside the study delimitation. The experiment did not test cross-vendor semantic alignment, multiple interacting industrial assets, long-term model drift, real telemetry quality, cybersecurity disturbances, operator-in-the-loop decisions, or production-scale latency. It also did not establish transferability to energy, transport, or other infrastructure domains. These issues define the next validation layer and are not claimed as demonstrated outcomes of the present laboratory case.

5.2 Recommendations

Further research may focus on field testing of the mechanism in real smart city circuits. It is worth involving several types of industrial assets and larger city models. It is also necessary to expand the scenario space and test the resilience to sensor data loss and latency. This will allow a more accurate assessment of the potential of the mechanism for practical implementation.

6. CONCLUSIONS

The study addressed the four research objectives within a controlled laboratory design. Transfer readiness identified 8 matches among 11 relevant elements, giving structural suitability of 0.72. IUDTTI increased from 0.46 for M1 to 0.73 for M2 and 0.88 for M3. For M3, semantic compatibility reached 0.91, functional integrity 0.92, and interoperability 0.88. ANOVA confirmed differences across the tested mechanism-scenario scores: $F(2,12) = 38.6$; $p < 0.001$; $\eta^2 = 0.86$. These findings answer RQ1–RQ4 and support H1 for the tested Simscape–DHALSIM configuration.

The scientific contribution lies in the transfer logic rather than in another interoperability taxonomy. Compared with interoperability frameworks [29–32], ontology and urban-data approaches [33, 34], and operational water-twin studies [39–41], the proposed mechanism evaluates how a ready Industrial Digital Twin can become an Urban Digital Twin runtime module. Its sequential chain combines semantic mapping, state translation, function wrapping, KPI translation, urban binding, runtime integration, and feedback recalibration. This enables joint preservation of state meaning, fault logic, functions, scenarios, and decision-support semantics.

A second contribution is the integrated evaluation of transfer quality through IUDTTI. The index combines semantic compatibility, functional integrity, fault-state coverage, scenario coverage, and interoperability within one normalized assessment. In this study, IUDTTI was used as a laboratory comparison criterion rather than as a universal standard. Its value is therefore in making the trade-off between data transfer and model-behaviour preservation explicit and reproducible.

The evidence remains limited to one industrial pump twin, one DHALSIM network, one deployment point, and five urban scenarios. Therefore, the results demonstrate controlled proof-of-concept performance, not general field effectiveness. Cross-vendor interoperability, multi-asset interaction, telemetry noise, latency, cybersecurity, operator decisions, and other infrastructure domains remain open issues. Field validation with real telemetry and operational constraints is required before practical claims can be extended beyond the tested water-infrastructure context.

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