Sunfish: Enabling Predictive Analytics for Datacenters Through Digital Twinning

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Motivation

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Context

21st century datacenters (DC) are mostly heterogeneous [8] and modern computational needs of AI drive managers to diversify datacenters even more [1]. In result datacenters become extremely complex and hard to operate with millions of CPU's, GPU's etc.

Figure 1.1: Society depends on datacenters to keep running, and therefore we cannot afford to let these systems break down or experience significant performance-related issues. With millions of servers in the largest datacenters, real-time management becomes very difficult. Left to right: a Google datacenter, server racks, Ada Lovelace AD102 GPU architecture.

DCDT’s lack predictive analytics

We need Datacenter Digital Twins (DCDT) to be better able to detect and solve issues in critical ICT infrastructure [1]. However, DCDT’s are still actively developed and lack crucial features such as predictive analytics [9] to *e.g.,* prevent unexpected failures. With predictive analysis (*e.g.,* simulation) DCDT’s could save millions of lost $USD [11].

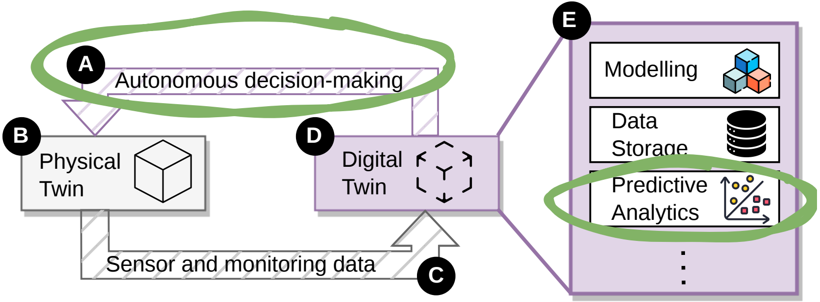

Figure 1.2: Where does our work fit within the field of datacenter digital twinning? There are 5 core elements to any Digital Twin: (A) The Digital → Physical Twin link, (B) the Physical Twin (*e.g.,* the datacenter), (C) the Physical → Digital Twin link, (D) the Digital Twin, (E) the features necessary to any Digital Twin. Highlighted areas are the contributions from this thesis, which include the autonomous actions resulting from predictive insights (A) and the predictive analysis itself within (E) .

Research Questions

Main Research Question

How to enable predictive analytics for datacenters through digital twinning?

Research Question 1

How to asses the current state-of-the-art of digital twinning for datacenters?

Research Question 2

How to design a reference architecture for a predictive datacenter digital twin using discrete-event simulation?

Research Question 3

How to evaluate and validate a datacenter digital twin architecture in relation to system requirements?

RQ1: Literature Review I

Results

The literature on DCDTs is scarce. Some systems barely classify as DTs (*e.g.,* Kalibre [13], ChatTwin [7]). Existing deployments specialize in Cooling and Heat Modelling, together with 3D visualizations. Most lack crucial predictive DC behaviour modelling.

Project	Simulation Technique	Focus	Stakeholders	Modelling Capability
ExaDigiT [2]	CFD/HT, AI/ML	Energy Loss Prediction, Heat Modelling	HPC Engineers and Operators	3D*, CH*, VP*, PE*, RA, SE‡
SmartDC [14]	CFD/HT, BIM, AI/ML	Heat Modelling, PUE optimization	Cloud Datacenter Engineers	CH‡, PE, 3D*
DyTwin [10]	Gaussian Process Regression, AI/ML	Anomaly Detection	Cloud Datacenter Operators	A*, FD, VP*, SE‡
ChatTwin [7]	**?**	Digital Twin Definition Language	Cloud Datacenter Engineers	3D*
Reducio [3]	POD, Gaussian Process Modelling (ML)	Heat Modelling	Edge and Hyper-scale Datacenter Operators	CH*, 3D*, SE
NetGraph [5]	Graphs	Network Management	Cloud Datacenter Operators	VP*, RA*, N*, SE‡
Kalibre [13]	CFD/HT, ML	Heat Modelling	Cloud Datacenter Engineers	CH*, 3D*

Table 1.1: Comparison of selected datacenter digital twins. **Modelling capability:** 3D = Visualizations; CH = Cooling/Heat, PE = Power/Energy Consumption, A = Anomaly Detection, N = Network Modelling, SE = Scenario Exploration, VP = Virtual Prototyping, FD = Federation, RA = Resource Allocation; **Data Analytics**: $*$ = Predictive Analysis; $\star$ = Descriptive Analysis, $\ddagger$ = Prescriptive Analysis.

A holistic DCDT system model

We propose a generic model of datacenter digital twinning that can be mapped to each system from **Table 1.1**. To answer **RQ2**, we design a ref. arch. for *Operations Model*.

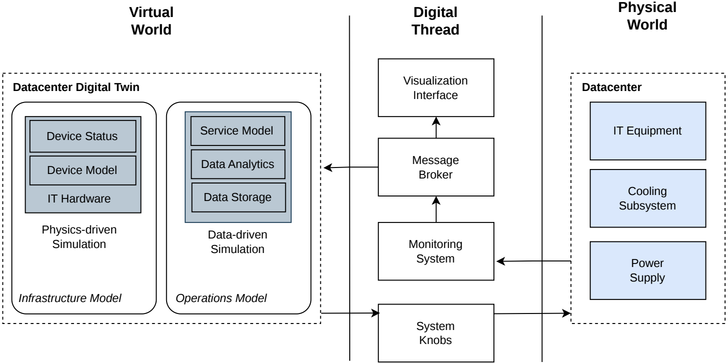

Figure 1.3: To answer **RQ1** we designed a generic datacenter digital twin system model based on a comprehensive literature review and findings from **Table 1.1**. The *Infrastructure Model* simulates the structure of the DC and the *Operations model* simulates the behaviour of the DC.

RQ2: Reference Architecture

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Use cases

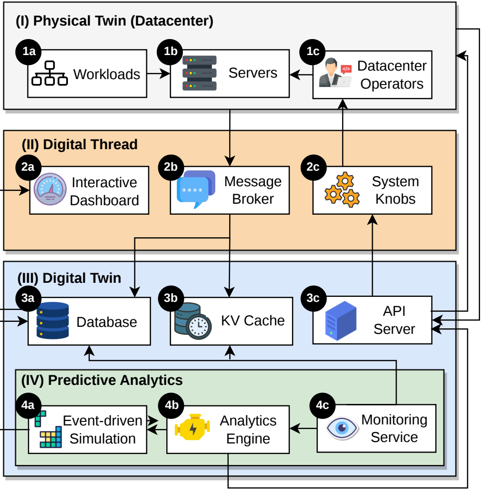

Figure 1.4: The predictive datacenter digital twin architecture. The time-series data flows initially to the `Kibana` dashboard, `PostgreSQL` database and `Redis` cache, as suggested in [10].

Main Finding I

On average, *Sunfish* achieves 12.17% less failures per task than baseline (OpenDC). Insights from predictive digital twinning yield noticeable performance difference.

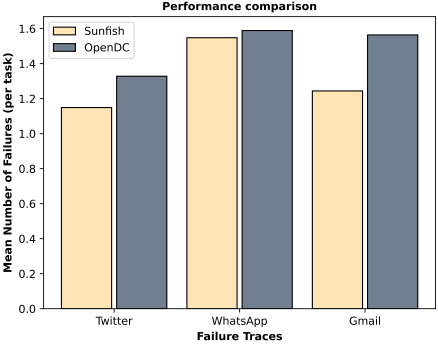

Figure 1.5: Experiment 1 – on the *x*-axis are different community failure traces. On the *y*-axis is the mean number of times a task has failed, during the entire workload. Vertical bars is standard deviation, measured over 5 repetitions.

RQ3: Experimental Results II

Main Finding II

Here explain what did you find.

Key Takeaways

What is the societal context?

What problem did we solve?

How did we solve this problem?

What did we find?

What do we see in future work?

Extra Slides: References I

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Extra Slides: Societal Impact

Why is this research important today?

Over 3 million jobs in the Netherlands directly depend on cloud services, which are hosted in datacenters [6]. Already the rapid expansion of datacenters has increased the presence of service failures across all cloud services [11]. We need to act now.

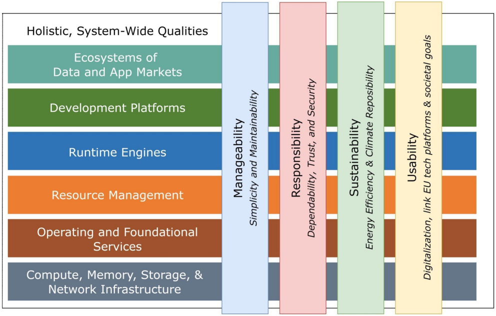

Figure E.1: Horizontally: the most important research areas in computer science in Netherlands. Vertically: qualities we should ensure across all research areas with the most outstanding impact on society. Datacenter manageability is a top-priority [6].

Extra Slides: Why Digital Twinning?

Definition

A DCDT mirrors the structure, context and behaviour of a datacenter [1]. The prerequisite to any digital twin is good monitoring and sensing capabilities in the physical entity. Datacenters meet this requirement easily because they already connect hundreds of monitoring sensors.

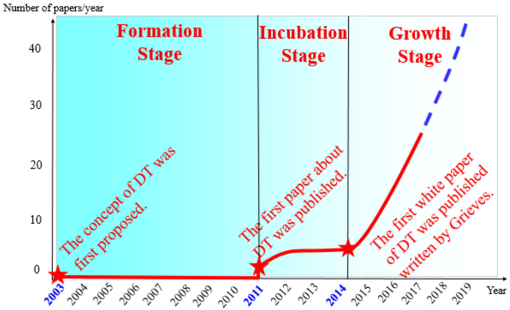

Figure E.2: Due to insufficient technological foundations, little work is available on DTs between 2003 and 2018, and it is only with the rapid growth of cloud computing, Internet-of-Things and Big Data analytics that DTs have reemerged [12]. That is why nobody used digital twins to mirror datacenters earlier.

Extra Slides: Why not pure simulation?

Predicting job failures

Preventing failure-caused outages in advance can reduce huge operational costs, as over 20% of all reported outages amount to more than 1 million US$ [4]. Only a constant bi-directional interaction (digital twin $\Longleftrightarrow$ physical entity) can achieve this.

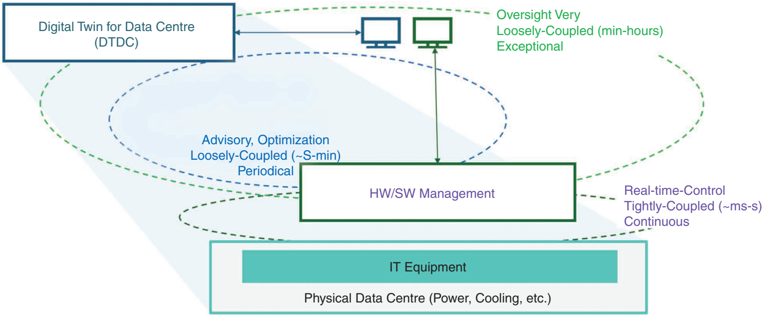

Figure E.3: Real-time control that is tightly-coupled with the IT equipment is a prerequisite for timely predictions within seconds/minutes [1].