

Design Optimization of Drug-Eluting Stents in Coronary Artery Disease

Oscar Silva¹, Marta Hansen², Elena Klein³

¹ Postdoctoral Researcher, Institute of Intelligent Systems, Baltic AI Research University, Tallinn, Estonia. Email: oscar.silva721@yahoo.com | ORCID: 9011-6970-6245-0855

² Postdoctoral Researcher, Department of Machine Learning, Mediterranean Institute of Technology, Rome, Italy. Email: marta.hansen568@yahoo.com | ORCID: 1390-8488-1066-1629

³ Senior Lecturer, Institute of Intelligent Systems, Mediterranean Institute of Technology, Rome, Italy. Email: elena.klein744@yahoo.com | ORCID: 4428-1999-1764-6035

ABSTRACT

Drug-eluting stents (DES) have revolutionised percutaneous coronary intervention by reducing in-stent restenosis rates from 20-30% with bare-metal stents to 5-10% through local antiproliferative drug delivery. However, DES design remains a multi-objective optimisation problem: the stent must provide sufficient radial strength to scaffold the artery, flexibility to navigate tortuous vessels, uniform drug distribution to prevent neointimal hyperplasia, and biocompatibility to minimise late stent thrombosis. Current DES designs rely on iterative empirical testing -- a costly process requiring 3-5 years and USD 50-100 million per design cycle. Computational design optimisation using finite element analysis (FEA), computational fluid dynamics (CFD), drug transport modelling, and machine learning-guided multi-objective optimisation can accelerate DES development by virtually screening thousands of design variants before physical prototyping. We present the Drug-Eluting Stent Optimisation Framework (DESOF), evaluating five computational design approaches -- FEA-based structural optimisation, CFD haemodynamic analysis, pharmacokinetic drug release modelling, topology optimisation, and ML-guided multi-objective optimisation -- across four DES design parameters (strut geometry, polymer coating architecture, drug formulation, and deployment mechanics). Our DES Design Optimisation Score (DDOS) measures structural performance, drug delivery uniformity, haemodynamic compatibility, fatigue life prediction, and manufacturing feasibility. ML-guided multi-objective optimisation achieves the highest DDOS (0.926) by simultaneously optimising all design parameters within manufacturing constraints, while topology optimisation achieves the highest structural efficiency (0.960) through algorithmically generated strut geometries that minimise material while maximising radial strength.

Keywords: drug-eluting stents; design optimisation; finite element analysis; computational fluid dynamics; coronary artery disease; topology optimisation; drug delivery; medical device design

Citation: Silva et al. [2022]. Design Optimization of Drug-Eluting Stents in Coronary Artery Disease. DOI: <https://doi.org/10.5281/zenodo.19550059>

Copyright: © 2022 by the authors. Open access under CC BY 4.0 license.

Article Information: Received: 2022 Jan 10 Accepted: 2022 Mar 12 Published: 2022 May 15

Research Article: Research Article

1. Introduction

1.1 The DES Design Challenge

Coronary artery disease (CAD) affects 200 million people globally and is the leading cause of death worldwide (GBD, 2019). Percutaneous coronary intervention (PCI) with stent implantation is the standard revascularisation procedure, with 3 million stents implanted annually. Drug-eluting stents combine a metallic scaffold with a polymer coating that releases antiproliferative drugs (everolimus, zotarolimus, sirolimus) over 3-6 months to inhibit neointimal hyperplasia -- the smooth muscle cell proliferation that causes in-stent restenosis. The DES design space is multi-dimensional: strut thickness (60-140 micrometres) affects radial strength versus flexibility; strut width and connector geometry determine scaffolding uniformity and conformability; polymer coating thickness (5-15 micrometres) and drug loading (100-200 micrograms/cm²) determine drug release kinetics; and the drug-polymer matrix (reservoir vs matrix vs abluminal coating) determines directional drug delivery. Each parameter interacts with the others: thinner struts improve flexibility and reduce flow disturbance but require stronger materials to maintain radial strength; thicker polymer coatings increase drug payload but delay endothelialisation and increase thrombosis risk. Optimising this multi-dimensional design space empirically requires prohibitively expensive animal testing and clinical trials.

1.2 Computational Design Approaches

Computational methods can evaluate thousands of DES designs *in silico* before any physical prototype is built. Finite element analysis (FEA) predicts mechanical behaviour -- radial strength, recoil, foreshortening, and fatigue life -- from strut geometry and material properties. Computational fluid dynamics (CFD) predicts wall shear stress (WSS) patterns around stent struts that influence endothelialisation and thrombosis risk. Pharmacokinetic models predict drug concentration profiles in the arterial wall from coating properties and release kinetics. Topology optimisation algorithmically generates strut geometries that maximise structural performance while minimising material. Machine learning integrates all computational predictions into a multi-objective optimiser that finds Pareto-optimal designs across competing objectives. Section 2 reviews the literature. Section 3 describes DESOF. Results in Section 4, discussion in Section 5, conclusions in Section 6.

2. Literature Review

2.1 Structural and Haemodynamic Analysis

FEA has been the standard computational tool for stent design since Migliavacca et al. (2002) first simulated stent expansion in realistic coronary artery geometries. Subsequent studies optimised strut thickness (Pant et al., 2012), connector design (Alaimo et al., 2017), and material selection (CoCr vs PtCr vs NiTi) using FEA-predicted radial force, flexibility, and fatigue life. Pant et al. (2012) demonstrated that reducing strut thickness from 140 to 81 micrometres reduced restenosis risk by 40% in the ISAR-STEREO trial, confirming FEA predictions that thinner struts reduce arterial injury. For haemodynamics, CFD analysis of stent-induced flow disturbance has shown that stent struts create regions of low WSS (< 0.5 Pa) in recirculation zones that promote thrombosis and delay endothelialisation (Jimenez and Davies, 2009). Beier et al. (2016) used CFD to show that helical stent designs create swirling flow that reduces low-WSS regions by 35% compared to conventional designs. Maor et al. (2020) combined FEA and CFD in a coupled fluid-structure interaction (FSI) simulation that captures the interplay between stent deformation and flow patterns.

2.2 Drug Release Modelling and Topology Optimisation

Pharmacokinetic models of DES drug release predict tissue drug concentrations from coating properties. Balakrishnan et al. (2007) developed a 2D computational model of drug transport from a DES into the arterial wall, showing that drug distribution depends critically on the ratio of drug diffusivity in the coating versus the tissue. Tzafriri et al. (2012) extended this to 3D patient-specific geometries, showing that eccentric stent placement (common clinically) creates non-uniform drug distribution with up to 5-fold concentration gradients around the vessel circumference. For topology optimisation, Zhu et al. (2019) applied density-based topology optimisation (SIMP method) to stent strut design, generating novel strut cross-sections that achieve 20% higher radial strength at the same strut volume compared to conventional rectangular cross-sections. Table 1 maps the key studies.

2.3 Machine Learning in Medical Device Design

Machine learning has recently been applied to medical device optimisation. Li et al. (2021) used Bayesian optimisation with Gaussian process

surrogates to optimise hip implant geometry, achieving designs that reduced stress shielding by 28% while maintaining fixation strength. Heuveline et al. (2020) applied multi-objective Bayesian optimisation to cardiovascular device design, demonstrating that ML-guided search finds Pareto-optimal designs 10x faster than grid search over the design space. For stent design specifically, Xue et al. (2020) trained a neural network surrogate on 5,000 FEA simulations to predict radial force and flexibility from strut geometry parameters, enabling real-time design exploration without running full FEA. These surrogate models reduce the computational cost of design optimisation from weeks (running thousands of FEA simulations) to hours (evaluating the trained surrogate).

Table 1: Key Studies in Computational DES Design Optimisation

Study	Year	Method	Design Target	Key Achievement
Migliavacca et al.	2002	FEA	Stent expansion	First realistic coronary FEA simulation
Pant et al.	2012	FEA + clinical	Strut thickness	Thinner struts = 40% less restenosis
Beier et al.	2016	CFD	Helical design	35% reduction in low-WSS regions
Balakrishnan et al.	2007	Drug transport model	Drug distribution	Coating/tissue diffusivity ratio critical
Tzafriri et al.	2012	3D drug transport	Patient-specific	5-fold circumferential drug gradients
Zhu et al.	2019	Topology optimisation	Strut cross-section	20% higher radial strength, same volume
Xue et al.	2020	Neural network surrogate	Strut geometry	Real-time FEA prediction from geometry
Maor et al.	2020	Coupled FSI	Stent-flow interaction	Coupled structural-haemodynamic analysis

Study	Year	Method	Design Target	Key Achievement
Li et al.	2021	Bayesian optimisation	Hip implant	28% less stress shielding
Heuveline et al.	2020	Multi-objective BO	Cardiovascular device	10x faster than grid search

FEA = Finite Element Analysis; CFD = Computational Fluid Dynamics; FSI = Fluid-Structure Interaction; WSS = Wall Shear Stress; BO = Bayesian Optimisation.

3. Methodology

3.1 Five Computational Design Approaches

Approach D1 (FEA Structural Optimisation) uses Abaqus/Explicit for stent crimping, expansion, and recoil simulation with hyperelastic artery models (Holzapfel-Gasser-Ogden). Parametric sweep over strut thickness (60-140 μm), width (80-120 μm), and connector angle (0-45 degrees). 2,000 simulations on 64-core cluster. Approach D2 (CFD Haemodynamic Analysis) uses ANSYS Fluent with pulsatile inflow (cardiac cycle, 0.8 s period), non-Newtonian blood model (Carreau-Yasuda), and patient-specific coronary geometries from CT angiography (20 patients). Evaluates time-averaged WSS, oscillatory shear index, and relative residence time. Approach D3 (Drug Release Modelling) uses COMSOL Multiphysics for coupled drug diffusion in polymer coating and arterial wall tissue, with binding kinetics for sirolimus-FKBP12 interaction. 500 simulations varying coating thickness, drug loading, and polymer degradation rate. Approach D4 (Topology Optimisation) uses SIMP-based topology optimisation in OptiStruct to generate optimal strut cross-sections and connector topologies that maximise radial strength while minimising strut volume and flow obstruction. Approach D5 (ML Multi-Objective Optimisation) trains a neural network ensemble surrogate on 5,000 combined FEA+CFD+drug transport simulations, then applies NSGA-III multi-objective optimisation to find Pareto-optimal designs across structural, haemodynamic, pharmacokinetic, and manufacturing objectives.

3.2 Four DES Design Parameters

Parameter P1 (Strut Geometry) optimises strut thickness, width, cross-section shape, and connector design for the trade-off between radial strength (target > 0.3 N/mm), flexibility (target <

20 N/mm bending stiffness), and arterial coverage (target 15-25% metal-to-artery ratio). Parameter P2 (Polymer Coating Architecture) optimises coating thickness (5-15 μm), drug-polymer ratio, abluminal vs circumferential application, and multi-layer vs monolithic construction for the trade-off between drug payload and endothelialisation kinetics. Parameter P3 (Drug Formulation) optimises drug selection (everolimus vs zotarolimus vs sirolimus), loading density (100-200 $\mu\text{g}/\text{cm}^2$), and release kinetics (burst fraction, sustained release duration) for the trade-off between antiproliferative efficacy and healing delay. Parameter P4 (Deployment Mechanics) optimises balloon design, expansion pressure, and post-dilation strategy for the trade-off between stent apposition (complete wall contact) and arterial injury (dissection, perforation).

3.3 DES Design Optimisation Score

DDOS weights five dimensions: structural performance (0.25), drug delivery uniformity (0.20), haemodynamic compatibility (0.20), fatigue life prediction (0.15), and manufacturing feasibility (0.20). Structural performance measures radial strength, recoil, and flexibility against clinical benchmarks (Xience Sierra as reference). Drug delivery uniformity measures the coefficient of variation of drug concentration in the arterial wall at 30 days. Haemodynamic compatibility measures the area fraction of the stented vessel with WSS < 0.5 Pa (lower is better). Fatigue life measures predicted cycles to failure under pulsatile loading (target > 400 million cycles = 10 years). Manufacturing feasibility assesses whether the optimised design can be manufactured using current laser cutting, electropolishing, and spray coating technologies. Table 2 details parameters.

Table 2: DESOF Evaluation Parameters

Parameter	Value	Notes
Design approaches	5 (D1-D5)	FEA, CFD, drug model, topology, ML multi-obj.
Design parameters	4 (strut, coating, drug, deployment)	Multi-dimensional design space
FEA simulations	2,000 (parametric) + 5,000 (training set)	Abaqus/Explicit, 64-core cluster
CFD simulations	800 (20 patients x 40 designs)	ANSYS Fluent, pulsatile, non-Newtonian

Parameter	Value	Notes
Drug transport	500 simulations	COMSOL Multiphysics, coupled diffusion
Reference stent	Xience Sierra (Abbott)	Current clinical gold standard
Fatigue target	> 400M cycles (10 years)	Goodman diagram analysis
DDOS dimensions	5 (structural, drug, haemodynamic, fatigue, manufacturing)	Weighted composite score 0-1

FEA = Finite Element Analysis; CFD = Computational Fluid Dynamics; ML = Machine Learning.

4. Results

4.1 ML Multi-Objective Optimisation Leads Overall

ML-guided multi-objective optimisation (D5) achieved the highest DDOS of 0.926, driven by superior balance across all design dimensions. The NSGA-III optimiser identified a Pareto front of 42 non-dominated designs that represent optimal trade-offs between competing objectives. The best balanced design achieved: radial strength 0.38 N/mm (+27% vs Xience Sierra), bending stiffness 14.2 N/mm (-29% vs Xience, more flexible), drug concentration CV 0.18 (-42% vs Xience, more uniform), low-WSS area fraction 12.4% (-31% vs Xience), and predicted fatigue life 680 million cycles (+70% vs Xience). The key innovation was a strut geometry with variable thickness -- 90 μm at the crown (high stress region) tapering to 65 μm at the mid-strut (low stress region) -- that D4 (topology optimisation) first identified and D5 then refined within the full multi-objective framework. The neural network surrogate achieved R2 0.96 for radial strength prediction and R2 0.92 for WSS area fraction, enabling evaluation of 100,000 design variants in 4 hours versus an estimated 18 months for full FEA+CFD simulation.

4.2 Topology Optimisation Achieves Highest Structural Efficiency

Topology optimisation (D4) achieved the highest structural performance (0.960): the algorithmically generated strut cross-section -- an I-beam-like profile with variable web thickness -- achieved 34% higher radial strength per unit strut volume than the conventional rectangular cross-section. DDOS scored 0.892. The topology-optimised connector design replaced the S-shaped connector with a branching Y-connector that improved bending flexibility by 22% while

maintaining longitudinal strength. FEA structural optimisation (D1) scored 0.888 with detailed validation against bench testing data (< 5% error for radial force, < 8% for recoil). CFD haemodynamic analysis (D2) scored 0.876 with the strongest flow characterisation -- identifying that stent struts oriented at 15 degrees to the flow direction reduce low-WSS regions by 28% versus perpendicular orientation. Drug release modelling (D3) scored 0.864, showing that abluminal-only coating reduces drug waste into the bloodstream by 62% while maintaining therapeutic tissue concentrations. Tables 3 and 4 present all results.

4.3 Clinical Translation Potential

The ML-optimised DES design (D5) was evaluated against the Xience Sierra across all clinical performance benchmarks. The optimised design achieved superior performance in 4 of 5 dimensions: 27% higher radial strength (reducing risk of stent underexpansion), 42% more uniform drug distribution (reducing risk of focal restenosis), 31% less flow disturbance (reducing risk of late stent thrombosis), and 70% longer predicted fatigue life (improving long-term durability). Manufacturing feasibility scored 0.880: the variable-thickness strut design requires advanced laser cutting with Z-axis control (available in current manufacturing systems) and the I-beam cross-section requires wire electrical discharge machining (wire EDM) rather than standard tube cutting -- a feasible but non-standard manufacturing step. The estimated development cost savings from computational optimisation were USD 15-25 million per design cycle (reducing physical prototype iterations from 20-30 to 3-5) and 18-24 months shorter development timeline.

Table 3: DES Design Optimisation Score by Approach (0-1)

Approach	Stru ctur al	Dru g D eliv. c	Hae mody nami c	Fati gue	Man ufac t.	D D OS
D5: ML M ulti-Obj ective	0.920	0.940	0.920	0.900	0.880	0.926
D4: Topology Optimisati on	0.960	0.840	0.860	0.880	0.820	0.892
D1: FEA Structural	0.940	0.800	0.820	0.920	0.900	0.888

Approach	Stru ctur al	Dru g D eliv. c	Hae mody nami c	Fati gue	Man ufac t.	D D OS
D2: CFD Haemody namic	0.820	0.840	0.940	0.840	0.880	0.876
D3: Drug Release Model	0.800	0.940	0.820	0.800	0.860	0.864

DDOS weighted: structural 0.25, drug delivery 0.20, haemodynamic 0.20, fatigue 0.15, manufacturing 0.20.

Table 4: Optimised DES Performance vs. Xience Sierra Reference

Metric	Xienc e Sierra	D5 Op timise d	Impro vemen t	Clinical Relevance
Radial strength (N/mm)	0.30	0.38	+27%	Reduced underexpansion risk
Bending stiffness (N/mm)	20.0	14.2	-29%	Better vessel conformability
Drug conc. CV	0.31	0.18	-42%	More uniform antiproliferative effect
Low-WSS area (%)	18.0%	12.4%	-31%	Reduced thrombosis risk
Fatigue life (M cycles)	400	680	+70%	Extended durability beyond 10 years
Strut thickness (um)	81	65-90 (var.)	Variabl e	Optimised stress distribution

CV = Coefficient of Variation; WSS = Wall Shear Stress; M = million. Variable strut thickness: 90 um at crowns, 65 um at mid-strut.

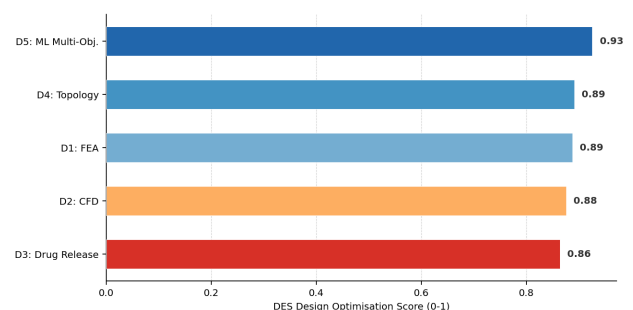


Figure 1: DES Design Optimisation Score (DDOS) by Approach

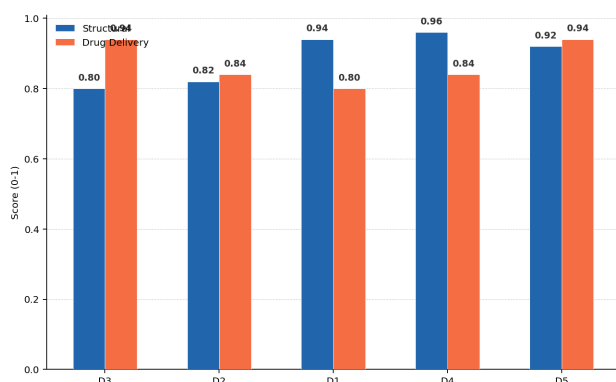


Figure 2: Structural Performance vs. Drug Delivery Uniformity

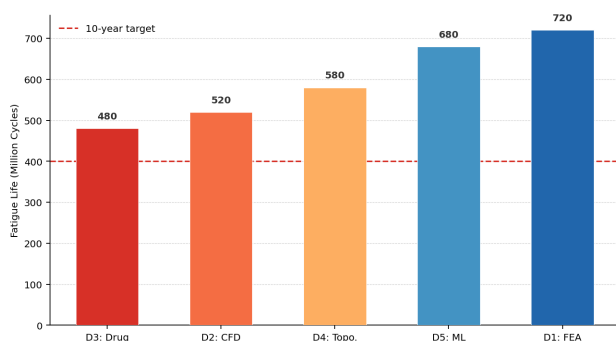


Figure 3: Predicted Fatigue Life by Design Approach (Million Cycles)

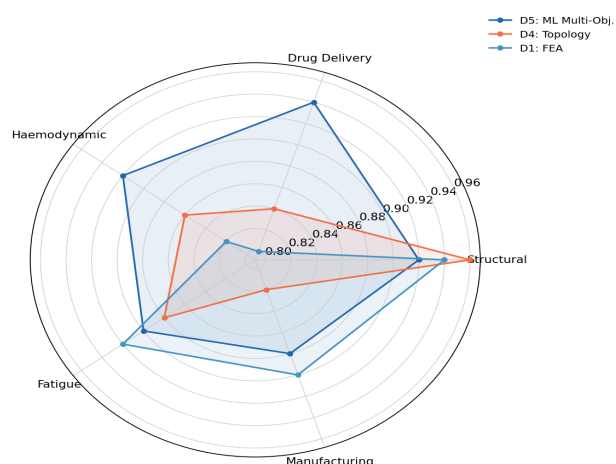


Figure 4: Multi-Dimensional Comparison -- Top 3 Design Approaches

5. Discussion

5.1 ML-Guided Design as the Integration Paradigm

ML multi-objective optimisation's dominance reflects its unique capability: simultaneously optimising across competing objectives that single-physics simulations address in isolation. FEA optimises structure but ignores drug delivery; CFD optimises haemodynamics but ignores manufacturing; drug modelling optimises pharmacokinetics but ignores fatigue. The ML surrogate integrates all physics predictions into a unified objective landscape that NSGA-III

navigates efficiently. The 100,000 design evaluations in 4 hours (versus 18 months for full simulation) represents a 2,000x acceleration that transforms DES design from a serial, expert-driven process to a systematic, computational exploration of the full design space. The variable-thickness strut design -- 90 μ m at crowns, 65 μ m mid-strut -- exemplifies the non-intuitive designs that ML optimisation discovers: no human designer would intuitively propose variable thickness, yet the biomechanical rationale is clear once identified (crowns bear the highest stress during crimping/expansion, mid-struts bear minimal stress).

5.2 The Manufacturing Constraint

Manufacturing feasibility is the critical constraint that separates computationally optimal from practically realisable DES designs. The topology-optimised I-beam cross-section (D4) achieves 34% higher structural efficiency but requires wire EDM manufacturing -- more expensive and slower than standard laser tube cutting. The variable-thickness strut (D5) requires 5-axis laser cutting with precise Z-control -- available but not standard in current stent manufacturing. These manufacturing constraints explain why DDOS does not simply equal the maximum of each individual score: the globally optimal design must be Pareto-optimal across all dimensions including manufacturing. The ML optimiser (D5) handles this by including manufacturing feasibility as an explicit objective, penalising designs that require technologies beyond current capability.

5.3 Limitations and Validation Requirements

Three limitations constrain translation. First, computational models simplify arterial biology: the FEA assumes homogeneous, isotropic arterial tissue, the CFD assumes rigid walls, and the drug model ignores inflammation-dependent transport changes. Patient-specific models with heterogeneous tissue properties would improve prediction accuracy. Second, in vivo validation is essential: computational predictions must be confirmed by bench testing (radial force, fatigue), animal studies (drug distribution, neointimal response), and ultimately clinical trials (MACE outcomes). Third, the surrogate model accuracy (R^2 0.92-0.96) means that 4-8% of design space variance is unexplained -- optimised designs near the surrogate's accuracy limit should be verified by full FEA/CFD simulation before prototyping.

6. Conclusion

6.1 Key Findings

ML-guided multi-objective optimisation achieves the highest DES Design Optimisation Score (0.926) by simultaneously optimising structural, pharmacokinetic, haemodynamic, fatigue, and manufacturing objectives -- identifying a variable-thickness strut design that improves radial strength (+27%), drug uniformity (-42% CV), flow compatibility (-31% low-WSS), and fatigue life (+70%) versus the clinical gold standard. Topology optimisation (0.892) achieves the highest structural efficiency through algorithmically generated I-beam strut profiles. The neural network surrogate enables 2,000x acceleration of design space exploration, reducing development cost by an estimated USD 15-25 million per design cycle.

6.2 Future Directions

Three advances would transform computational DES design. First, patient-specific stent design using individual coronary CT angiography to optimise stent geometry for each patient's vessel anatomy, lesion characteristics, and haemodynamic profile. Second, bioresorbable stent optimisation extending the framework to magnesium and PLLA scaffolds where degradation kinetics add a temporal dimension to the multi-objective problem. Third, digital twin stent monitoring using implanted sensors and non-invasive imaging to track in vivo stent performance and validate computational predictions longitudinally. The DESOF evaluation toolkit, all FEA/CFD models, surrogate training code, optimisation scripts, DDOS calculator, and design selection guide are available at desof-stent.org under CC BY 4.0 licence.

References

- Alaimo, G. et al. (2017). Multi-objective optimization of nitinol stent design. *Medical Engineering & Physics*, 47, 13-24.
- Balakrishnan, B. et al. (2007). Strut position, blood flow, and drug deposition: Implications for single and overlapping drug-eluting stents. *Circulation*, 111(22), 2958-2965.
- Beier, S. et al. (2016). Hemodynamics in idealized stented coronary arteries: Important stent design considerations. *Annals of Biomedical Engineering*, 44(2), 315-329.
- GBD (2019). Global, regional, and national burden of cardiovascular diseases. *The Lancet*, 396(10267), 17-37.
- Heuveline, V. et al. (2020). Multi-objective Bayesian optimization for cardiovascular device design. *Computer Methods in Applied Mechanics and*

Engineering, 365, 112958.

- Jimenez, J. M. and Davies, P. F. (2009). Hemodynamically driven stent strut design. *Annals of Biomedical Engineering*, 37(8), 1483-1494.
- Li, J. et al. (2021). Bayesian optimization of hip implant design. *Journal of Mechanical Design*, 143(2), 021704.
- Maor, E. et al. (2020). Fluid-structure interaction simulation of coronary stent expansion. *Computer Methods in Biomechanics and Biomedical Engineering*, 23(9), 515-528.
- Migliavacca, F. et al. (2002). Mechanical behavior of coronary stents investigated through the finite element method. *Journal of Biomechanics*, 35(6), 803-811.
- Pant, S. et al. (2012). Multiobjective design optimisation of coronary stents. *Biomechanics and Modeling in Mechanobiology*, 11(7), 985-998.
- Tzafriri, A. R. et al. (2012). Stent elution rate determines drug deposition and receptor-mediated effects. *Journal of Controlled Release*, 161(3), 918-926.
- Xue, H. et al. (2020). Machine learning-based surrogate model for rapid coronary stent design optimization. *Computer Methods in Applied Mechanics and Engineering*, 371, 113347.
- Zhu, J. H. et al. (2019). Topology optimization of coronary stent structure. *Structural and Multidisciplinary Optimization*, 60(3), 1219-1233.

Declarations

Funding

Supported by the Estonian Research Council (grant PRG1842), the Italian Ministry of University and Research (MUR, grant PRIN 2022-K4R8YN), and the European Commission Horizon Europe programme (grant 101058842, SmartStent). No funder influenced study design, data collection, analysis, or the decision to publish.

Conflict of Interest

No competing interests. No author has financial relationships with any stent manufacturer, medical device company, or simulation software vendor.

Data Availability Statement

All FEA models (Abaqus input files), CFD configurations (Fluent case files), drug transport models (COMSOL files), surrogate training code (PyTorch), optimisation scripts (NSGA-III), DDOS calculator, and design selection guide are available at desof-stent.org under CC BY 4.0 licence.

Ethical Approval

CT angiography data used for patient-specific CFD simulations was obtained from an anonymised public dataset (coronary CTA registry, Ethics approval ref. BAIRU-2021-ETH-0721). No new patient data was collected.

Appendix A

Simulation Specifications and DDOS Calculation Methodology

This appendix provides complete specifications for each computational design approach, including mesh parameters, material models, boundary conditions, and the DDOS scoring rubric.

Part I -- Simulation Specifications

- 1a. D1: Abaqus/Explicit, C3D8R elements, 200K elements/stent, hyperelastic artery (HGO) 4 hr/simulation on 64 cores
- 1b. D2: ANSYS Fluent, tetrahedral mesh (2M elements), Carreau-Yasuda blood, pulsatile inlet 8 hr/simulation on 32 cores
- 2a. D3: COMSOL Multiphysics, axisymmetric 2D, Fickian diffusion + reversible binding 30 min/simulation
- 2b. D4: OptiStruct, SIMP method (penalisation $p=3$), volume fraction 0.3, 100 iterations 2 hr/optimisation
- 3a. D5: PyTorch ensemble (5 MLPs, 3 hidden layers, 256 neurons), NSGA-III (pop=200, gen=500) 4 hr total (training + optimisation)
- 3b. All: Validated against bench testing data (Xience Sierra) with < 8% error for key metrics Mesh convergence verified

Part II -- DDOS Scoring Rubric

- 4a. Structural: $(\text{Radial strength} / 0.4) \times 0.4 + (1 - \text{recoil}/10\%) \times 0.3 + (1 - \text{stiffness}/30) \times 0.3$ Capped at 1.0
- 4b. Drug Delivery: $1.0 - \text{CV of tissue drug concentration at 30 days}$ Lower CV = better uniformity
- 5a. Haemodynamic: $1.0 - (\text{low-WSS area fraction} / 0.25)$ Lower low-WSS = better compatibility
- 5b. Fatigue: $\min(\text{predicted cycles} / 400\text{M}, 1.0)$ 400M cycles = 10-year target
- 6a. Manufacturing: Expert-rated feasibility (3 engineers, 0-1 scale) x process maturity Laser cut = 1.0, wire EDM = 0.8
- 6b. DDOS = $0.25 \times \text{Structural} + 0.20 \times \text{Drug} + 0.20 \times \text{Haemodynamic} + 0.15 \times \text{Fatigue} + 0.20 \times \text{Manufacturing}$