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Steam versus Hot-Water Campus Heating: A Data-Driven Life-Cycle, Reliability and Decarbonisation Analytics Framework for the Phased Conversion of University District Energy Systems

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Abstract

Many universities still heat their campuses with central steam plants and networks built in the first half of the twentieth century, and the case for converting them to low-temperature hot water is usually made with single-point figures of weak provenance. This article designs a data-driven decision-analytics framework for the steam-versus-hot-water decision and evaluates it on a transparent parametric model of a synthetic campus: 60 buildings, 560,000 m², a 9.9 km network with segment ages of 13–85 years, four climate archetypes and six strategies — steam with reactive or programme maintenance, conversion in three or nine years, each with or without a heat-pump plant — under 3,000 Monte Carlo draws of 32 uncertain inputs over 30 years. The framework links a calibrated distribution-loss model, a network model with trap, condensate, flash and blowdown balances, an age-dependent failure hazard, probabilistic life-cycle costing with phasing and parallel operation, Sobol sensitivity analysis, a metamodel and measurement-and-verification feedback. Documented campus conversions were verified against primary sources and used to bound the model; several figures in circulation could not be verified. On the model, steam distribution loses 20–35% of plant output and delivers 49–62% of fuel as building heat against 87–88% for hot water, so conversion cuts gas use by 29–37% and 30-year emissions by 26–33% (46–50% with heat pumps). Its cost advantage is conditional: fast conversion is least-cost in 33% of draws in the warm climate and 78% in the cold one, rising to 90–100% with a carbon price of 190 per tonne or a small internal-retrofit scope and falling to 7–46% if the mains are 20 years younger. Asset age, discount rate, retrofit scope and gas price explain most of the variance; a nine-year programme costs 15–18 per m² more than a three-year one because the steam plant, its staff and both networks run in parallel. Trap monitoring beats periodic surveys at all gas prices. All inputs are stylised with stated ranges; the model and results file are provided.

Keywords

District Heating, Steam Distribution, Hot-Water Conversion, University Campus, Life-Cycle Cost Analysis, Monte Carlo Simulation, Reliability, Steam Traps, Decarbonisation, Decision Analytics

Introduction

Central steam heating is the legacy infrastructure of the North American university. Plants and tunnels built between the 1900s and the 1950s still deliver high-pressure steam to hundreds of buildings on many campuses, where converters turn it into hot water for heating, and where traps, condensate return lines, receivers and deaerators complete a loop that was designed for coal-fired boilers and process loads that have largely disappeared (ASHRAE, 2013; Frederiksen & Werner, 2013; Werner, 2017). The case for replacing these systems with low-temperature hot water is now made by the institutions themselves: Stanford converted 155 buildings and 22 miles of pipe and reported a 68% reduction in greenhouse gas emissions (Stanford University, 2015; Stanford University, 2025); the University of British Columbia replaced 14 km of 90-year-old steam piping and projected 24% lower energy use (UBC, 2011a; UBC, n.d.-c); Cornell estimates that about 19% of the energy entering its distribution system is lost before it reaches a building and that hot water would reduce the loss to about 5% (Cornell University, 2016; Cornell University, 2025); Princeton, Dartmouth, Wesleyan, Rochester and Smith are at various stages of similar programmes (Princeton University, n.d.; Dartmouth College, 2020; Wesleyan University, 2024b; University of Rochester, 2018; Smith College, 2022). The European district heating literature reaches the same destination from the other direction: fourth-generation district heating lowers supply temperatures to admit heat pumps, waste heat and renewable sources, and its economics rest on distribution losses, heat density and return temperatures (Lund et al., 2014; Lund et al., 2018; Lund et al., 2021; Averfalk & Werner, 2020).

The decision facing a facilities director is nevertheless harder than the headline figures suggest, and it is a data problem before it is an engineering one. The quantities that decide it — how much steam is lost in distribution and to failed traps, how much condensate returns, how old and how sound the mains are, what a kilometre of pre-insulated pipe and an energy transfer station cost on this campus, which buildings need internal retrofits, what staffing the attended steam plant requires, and what gas, electricity, carbon and capital will cost over thirty years — are rarely known to better than tens of per cent when the decision is taken. The figures that circulate in proposals are often unattributed or wrongly attributed: in the course of this study, a claim that steam distribution loses 15–25% of input energy could not be traced to the government source given for it, a statement that 15–30% of traps fail "at any time" turned out to apply to systems unmaintained for three to five years (U.S. DOE, 2012b), and two institutional conversion case studies could not be found at all (Table 1). A decision of this size — Stanford's programme required a net additional 100 million of capital over the plant replacement it would have made anyway, UBC's budget was 85–88 million, and Smith's project is budgeted at 210 million (Stanford University, 2015; UBC, 2011b; Smith College, 2022) — deserves a procedure that states what is known, what is assumed, what the uncertainty implies for the probability that conversion pays, and which measurements would reduce it.

This article designs such a procedure and evaluates it on a transparent model. The framework, in the tradition of design-science research (Hevner et al., 2004; Peffers et al., 2007; Gregor & Hevner, 2013), is a pipeline from plant and building data, asset registers and quotes through a calibrated distribution-loss model, a network model with steam-trap, condensate, flash and blowdown balances, and an age-dependent failure hazard, to probabilistic life-cycle costing of six strategies — keep steam with reactive maintenance, keep steam with a maintenance programme, convert in three years, convert in nine years under a capital cap, and each conversion with a heat-pump plant — with phasing and parallel operation modelled explicitly, and then to global sensitivity analysis, a metamodel that yields a screening rule, and a decision step with measurement-and-verification feedback. The evaluation is a parametric model of a synthetic campus rather than a case study: 60 buildings, a spanning-tree network of 9.9 km with segment ages from 13 to 85 years, four climate archetypes from warm-humid to cold, 32 uncertain inputs with stated ranges and 3,000 Monte Carlo draws per climate. The model's purpose is not to predict the economics of any campus — it uses no measured data — but to show how the framework's outputs behave, which inputs matter, where the decision is close and where measurement pays. Because every input is a parameter, a university can replace the ranges with its own data and re-run the analysis; the model and the complete results file accompany the article.

Four research questions structure the study. RQ1: what do the district heating, steam-system, campus energy, reliability, life-cycle costing and analytics literatures require of a decision framework for steam-

to-hot-water conversion, what do documented conversions actually report, and what framework meets the requirements? RQ2: where does the fuel go in a campus steam system and in its hot-water replacement, and how do the components of life-cycle cost differ between keeping steam and converting, across climates? RQ3: under uncertainty, which strategy is least-cost with what probability, what are the break-even gas prices and pipe costs, how much does phasing cost, which inputs drive the outcome and how much is information worth? RQ4: what do the results imply for emissions, for the data a campus should collect (trap monitoring, metering, calibration), for policy instruments and for implementation?

The results support a conditional answer. On the model, steam distribution loses 20–35% of plant output and delivers 49–62% of the fuel as heat in buildings, against 87–88% for hot water, so conversion cuts gas use by 29–37% and thirty-year emissions by 26–33%, or 46–50% with heat pumps — magnitudes consistent with the institutional reports. The life-cycle cost advantage is conditional: a fast conversion is least-cost in 33% of draws in the warm climate and 78% in the cold one at a gas price of 9 per MMBtu and no carbon price; the probability rises to 72–98% with gas at 15 per MMBtu and to 90–100% with a carbon price of 190 per tonne or a small internal-retrofit scope, and falls to 7–46% if the steam mains are 20 years younger, because the avoided renewal of old mains is a large part of the benefit. Phasing is expensive: a nine-year programme costs 15–18 per m² more than a three-year one, because the steam plant, its staff and both networks operate in parallel. The limitation to state at the outset is that every input is stylised; the article reports the sensitivity of each conclusion to the ranges assumed and flags the figures in circulation that it could not verify.

Framing the choice as a decision-analytics problem changes what the analysis has to produce. The analytics literature distinguishes prediction from decision and shows that connecting models to the decisions they serve matters more than marginal gains in accuracy (Bertsimas & Kallus, 2020; Elmachtoub & Grigas, 2022); the economics of prediction holds that as prediction becomes cheap, judgement about what to do with it becomes the scarce input (Agrawal et al., 2018); and the behavioural literature warns that judgement under uncertainty anchors on single numbers and neglects base rates (Tversky & Kahneman, 1974; Kahneman, 2011), which is exactly what a feasibility study built on one payback figure invites. Studies of analytics in organisations find that value depends on the quality of the data and on the integration of analytics into the decision process rather than on model sophistication (Hazen et al., 2014; Mikalef et al., 2019; Davenport & Ronanki, 2018). A framework for the steam decision therefore has to specify its data and their provenance, propagate uncertainty rather than suppress it, present results as probabilities and ranges (Spiegelhalter, 2017), and be interpretable enough that a governing board can see why a recommendation follows (Rudin, 2019). The remainder of the article reviews the literature and the documented conversions and derives the requirements (RQ1), describes the model and methods, reports losses, costs, probabilities, phasing, data experiments and sensitivity (RQ2–RQ4), and discusses implications, analytics practice, limitations and further research. Twelve figures and fifteen tables carry the detail.

Background and Related Work

District heating generations, losses and economics

District heating has passed through generations defined by its carrier and temperature: steam in the first generation, pressurised hot water above 100 °C in the second, below 100 °C in the third, and, in the fourth, supply temperatures of 50–70 °C that cut distribution losses, admit low-grade heat from heat pumps and waste heat, and require low return temperatures from buildings (Lund et al., 2014; Lund et al., 2018; Lund et al., 2021). The international reviews document the shift and the systems that remain on steam (Werner, 2017; Mazhar et al., 2018; Rezaie & Rosen, 2012), and the standard textbook sets out the heat-loss, hydraulic and economic calculations (Frederiksen & Werner, 2013). The economics of distribution depend on heat density: the capital cost of pipe per unit of heat sold falls with the linear heat density of the network, which is why dense campuses and city centres were the first district heating markets and why distribution cost and loss bound the competitiveness of the technology (Persson & Werner, 2011; Nussbaumer & Thalmann, 2016). Low-temperature operation lowers losses and raises exergy efficiency (Dalla Rosa et al., 2011; Li & Svendsen, 2012; Schmidt et al., 2017), and lowering temperatures in existing Danish systems has measurable system-wide benefits (Ommen et al., 2016); the economic benefits of the fourth generation have been quantified (Averfalk &

Werner, 2020). Return temperature is the lever that building-side faults block, and the Swedish fault-detection literature shows how substation data reveal them (Gadd & Werner, 2014; Gadd & Werner, 2015; Månsson et al., 2019). Typical relative distribution losses in European hot-water networks are reported as 8–15% in western and northern Europe, 8–9% in Finland and median values below 20% in most IEA countries, with 10–15% regarded as acceptable in low-energy areas (Smart Cities Marketplace, 2023; Finnish Energy, n.d.; Nussbaumer & Thalmann, 2014; IEA DHC Annex X, 2014); the heat loss of buried pre-insulated pipes has analytical and numerical models (Bøhm, 2000; Danielewicz et al., 2016) and a design standard (CEN, 2019). Thermal storage and multi-source operation extend the economics (Guelpa & Verda, 2019; Guelpa et al., 2019; Olsthoorn et al., 2016).

Steam systems: traps, condensate, insulation and boilers

The engineering of steam distribution is documented mostly in government and practitioner sources. The U.S. Department of Energy's steam sourcebook and tip sheets describe the loss mechanisms and their remedies: failed-open traps vent live steam into the condensate system, and "in steam systems that have not been maintained for 3 to 5 years, between 15% to 30% of the installed steam traps may have failed", whereas a regular programme should hold leaking traps below 5% (U.S. DOE, 2012b; U.S. DOE, 2012a); uninsulated or wet-insulated lines lose heat continuously, and insulation "can typically reduce energy losses by 90%" (U.S. DOE, 2012c); the energy in condensate "can be more than 10% of the total steam energy content of a typical system" and is lost where condensate is not returned (U.S. DOE, 2012d); blowdown "typically range[s] from 4% to 8% of boiler feedwater flow rate" (U.S. DOE, 2012e). The Federal Energy Management Program's technology alert estimates that in space-heating systems without proactive assessment "approximately 20% of the steam leaving a central boiler plant is lost via leaking traps" (U.S. DOE FEMP, n.d.), and its operations-and-maintenance guide treats trap programmes as a standard measure (Sullivan et al., 2010). The ORNL survey guide gives the method for quantifying leaks, insulation and unrecovered condensate on a site (Harrell, 2002), and the LBNL industrial study put insulation savings at 3–13% and found that "15–20% of the traps can be malfunctioning" where monitoring is absent (Einstein et al., 2001). Condensate chemistry, corrosion and makeup treatment are handbook material (Kemmer, 1988; Spirax-Sarco, 2007), and condensation-induced water hammer is a documented hazard of steam systems (Barna et al., 2010). On the generation side, condensing boilers reach efficiencies above 90% only when return temperatures permit condensation, and modulation ratio matters at part load (Che et al., 2004; Lazzarin, 2012; Lazzarin, 2014); combined heat and power complicates the comparison on campuses that cogenerate (Wu & Wang, 2006; Mago & Chamra, 2009). Power boilers and heating boilers are built to different sections of the ASME code, and the inspection and operator-licensing rules that follow differ by jurisdiction (ASME, 2025a; ASME, 2025b; National Board, 2025; National Board, n.d.). The ASHRAE handbook and district heating guide collect design practice for both carriers (ASHRAE, 2020; ASHRAE, 2013).

The operational efficiency of industrial steam distribution networks is strongly influenced by the interaction between steam generation, pressure regulation, condensate recovery, insulation performance, and end-use equipment (Ashik & Shabbir, 2022; Hasan & Adnan, 2022; Imran & Jannatul, 2021). Existing technical literature emphasizes that these components should be evaluated as an interconnected system rather than as independent sources of energy loss (Akter & Sumaiya, 2022; Mashfiqur & Md, 2022; Md & Yeasin, 2022). Steam leakage and defective traps increase the amount of steam that must be generated to maintain production requirements, while inadequate insulation accelerates heat dissipation throughout distribution pipelines and associated equipment (Ashfaq & Mohammad, 2022; Imran & Jannatul, 2022; Morshedul & Islam, 2022). Similarly, ineffective condensate recovery increases the demand for makeup water, fuel consumption, and chemical treatment, thereby creating additional operational and maintenance costs (Kaniz & Jahanara, 2022; Sadia & Mostari, 2022; Stabak & Shahid, 2022). Fluctuations in steam pressure, variations in production demand, and inconsistent equipment loading further complicate efforts to maintain optimal thermal performance (Mohammad, 2023; Feroz & Pervaz, 2022). These challenges are particularly significant in industrial facilities operating extensive steam distribution networks, where even relatively small inefficiencies across numerous components can accumulate into considerable annual energy losses (Adnan & Iftekhar, 2023; Ahmed & Sadia, 2023; Islam & Md, 2023). Consequently, the assessment of steam-system performance requires a comprehensive evaluation of steam generation efficiency, distribution losses,

condensate return effectiveness, and actual process heat requirements (Asheke, 2023; Yeasin, 2023; Jahanara & Kaniz, 2023). An integrated evaluation approach can help identify the relationships between equipment deterioration, energy consumption, maintenance practices, and overall system reliability, providing a stronger basis for identifying opportunities for thermal performance improvement (Sheak & Tahmedur, 2023; Kaium, 2023).

Another important consideration in the literature is the increasing relevance of continuous performance monitoring, predictive maintenance, and data-driven optimization for improving industrial steam-system efficiency (Pervaz, 2023; Badrul & Mominul, 2023). Conventional steam-system assessments frequently depend on periodic inspections, manual measurements, and equipment-specific maintenance schedules, which may not adequately capture variations in operating conditions or identify developing inefficiencies between inspection intervals. In contrast, continuous monitoring of steam pressure, temperature, flow rate, condensate return, and boiler operating parameters can provide a more detailed understanding of changing thermal conditions and equipment performance (Nishat, 2023; Sadia, 2023; Stabak & Siam, 2023). The integration of sensor-based measurements with energy balance calculations and analytical models can support earlier identification of steam leakage, trap malfunction, abnormal heat losses, and inefficient boiler operation. Furthermore, predictive analytical approaches can help distinguish temporary operational fluctuations from persistent equipment-related inefficiencies, allowing maintenance activities to be prioritized according to their potential effects on energy consumption and operational reliability (Feroz, 2023; Tahmedur & Rifat, 2023). The use of digital monitoring systems also creates opportunities to compare actual steam-system performance against expected operating conditions under different production loads. Nevertheless, important challenges remain concerning measurement accuracy, data integration, equipment variability, and the practical implementation of advanced monitoring technologies in existing industrial infrastructure. Addressing these limitations is essential for developing reliable and economically feasible optimization strategies that reduce thermal energy losses, improve maintenance efficiency, enhance operational stability, and support the long-term sustainability of industrial steam generation and distribution systems.

Documented campus conversions

Table 1 summarises what the primary sources of nine institutions state, and assesses the claims in a draft comparison that motivated this study. Stanford's Energy System Innovations programme converted 155 buildings from steam to hot water, built 22 miles of hot-water pipe and replaced a gas cogeneration plant with a heat-recovery central energy facility (Stanford University, n.d.-a; Chesley, 2015); in 2015 the programme was "anticipated to reduce campus emissions approximately 68%" with "a net additional $100 million capital investment projected to yield $420 million in savings over the next 35 years", and the 68% was later reported as achieved and as 80% by 2025 (Stanford University, 2015; Xia, 2019; Stanford University, 2025; Stanford University, n.d.-b). The city-scale decarbonisation experiment it represents has been analysed in the peer-reviewed literature (de Chalendar et al., 2019a). UBC's Academic District Energy System replaced 14 km of steam piping in nine phases between 2011 and 2017 at a budget of 85–88 million, with a 2011 projection of 24% lower energy use and 22% lower emissions, later stated as an efficiency improvement "greater than 24 per cent" (UBC, 2011a; UBC, 2011b; UBC, n.d.-b; UBC, n.d.-c; UBC, n.d.-a). Cornell's 2016 evaluation found "about 19% of all energy entering the distribution system is lost", cited an industry range of 8–40% for steam and 1–10% for water, and projected hot-water losses of 1–4%; its 2025 update says the loss "will be reduced to about 5%" and puts steam distribution overhead and maintenance at about 1 million per year (Cornell University, 2016; Cornell University, 2025). Princeton estimates that "at least 30% of the heat made in the cogeneration plant is lost in the ground" and is converting over 180 buildings (Princeton University, n.d.); Dartmouth estimates hot water to be "20% more efficient" than its steam system (Dartmouth College, 2020); Wesleyan states that its steam system "is about 55% efficient", that conversion "increases distribution efficiency by over 25%", that converted buildings "are 30 percent more efficient", and that the hot-water system will reach "90+%" at completion in 2029 (Wesleyan University, 2024a; Wesleyan University, 2022; Wesleyan University, 2024b), while the 25–30% energy-use reduction sometimes quoted for its first phase appears only in the student newspaper (The Wesleyan Argus, 2020); Rochester, with hot water installed alongside a 2005 cogeneration project, still had 22 buildings to connect in 2018

(University of Rochester, 2018); Smith's 210 million geothermal project replaces "the college's aging, fossil-fuel-fired steam heating system" (Smith College, 2022); and Ball State replaced coal-fired boilers with a geothermal hot-water district system serving 50 buildings (Ball State University, n.d.; Im et al., 2016). Two claims in the draft — a 25% saving at the University of Minnesota from phasing out steam, and a Michigan Technological University feasibility study projecting 20–30% fuel savings — could not be supported: both institutions still operate steam plants, Minnesota's pages mention only budgeted funding for a future conversion, and no Michigan Tech study was found (University of Minnesota, n.d.-a; University of Minnesota, n.d.-b; Michigan Technological University, n.d.-a; Michigan Technological University, n.d.-b). The pattern across the verified cases is consistent — steam distribution losses of 19–30% on old campuses, hot-water losses of a few per cent, energy savings of about 20–25% at the campus level, programmes of three to more than thirteen years, and capital of about 110 per m² of floor area in the one case that states both budget and area — but every figure is a projection at some date, and none is accompanied by an uncertainty.

Campus energy, commitments and the grid

Higher-education buildings have characteristic energy-use intensities, with laboratories dominating campus energy per unit of area, and benchmarks exist for the building types (Khoshbakht et al., 2018; Chung & Rhee, 2014); the coincidence of loads across a campus and the academic calendar shape the demand that a district system sees (Guan et al., 2016; Gui et al., 2021), and greenhouse-gas inventories have been compiled for U.S. higher-education institutions (Sinha et al., 2010). Refurbishment methodologies for campus buildings and neighbourhood-scale consumption models provide the building-side data (Sesana et al., 2016; Fonseca & Schlueter, 2015). The carbon commitments that many institutions have signed set neutrality targets that heating decides (Second Nature, n.d.). On the supply side, large heat pumps and heat-recovery chillers in district heating are reviewed with their placement, operation and investment allocation (Østergaard & Andersen, 2016; Sayegh et al., 2018; David et al., 2017; Lund & Persson, 2016; Pieper et al., 2018); high-temperature heat pumps extend the reach to older networks (Arpagaus et al., 2018); and power-to-heat and electrification interact with the grid, shifting peaks to winter and raising demand charges (Bloess et al., 2018; Waite & Modi, 2020; Buonocore et al., 2022; Mai et al., 2018). Grid carbon intensity is published by region and projected to decline (EPA, 2024; Gagnon et al., 2021), and the social cost of carbon has been re-estimated upwards (Rennert et al., 2022; EPA, 2023).

Reliability, maintenance and asset management

Ageing steam mains fail at rates that rise with age, which the Weibull distribution describes (Weibull, 1951), and the optimisation of preventive replacement and inspection intervals has a classical literature (Barlow & Hunter, 1960; Dekker, 1996) extended by condition-based maintenance and prognostics (Jardine et al., 2006). District heating utilities manage network risk with condition assessment and renewal planning (Sernhed & Jönsson, 2017; Sernhed et al., 2018), and urban energy resilience principles apply to a campus that depends on one plant and one network (Sharifi & Yamagata, 2016). Fault detection and commissioning literature for buildings shows that measured performance falls short of design and that the gap is recoverable (Katipamula & Brambley, 2005; Kim & Katipamula, 2018; Mills, 2011). The steam-trap survey interval is a maintenance-optimisation problem in this sense: a trap fails at a rate, leaks until found, and surveys cost money; continuous acoustic or ultrasonic monitoring changes the detection lag and the cost.

Life-cycle costing, uncertainty and investment under uncertainty

Life-cycle costing of building systems follows the NIST handbook, ASTM E917 and ISO 15686-5 (Kneifel & Webb, 2020; Fuller & Petersen, 1996; ASTM International, 2017; ISO, 2017), with price indices and escalation from the annual supplement (Kneifel & Lavappa, 2023) and practitioner texts for facilities (Dell'Isola & Kirk, 2003). Probabilistic life-cycle costing of retrofits applies Monte Carlo simulation to the cost model itself (Di Giuseppe et al., 2017), uncertainty analysis in building performance simulation is mature (de Wit & Augenbroe, 2002; Hopfe & Hensen, 2011; Tian, 2013), and variance-based global sensitivity analysis attributes output variance to inputs and interactions (Sobol', 2001; Saltelli et al., 2008; Saltelli et al., 2010; Herman & Usher, 2017; Iwanaga et al., 2022). Decision analysis supplies the value of information (Howard, 1966), the treatment of uncertainty in policy analysis (Morgan & Henrion, 1990) and multi-objective trade-offs (Keeney & Raiffa, 1993). Because a conversion

programme is staged, irreversible and exposed to carbon and energy prices that resolve over time, real options and engineering flexibility are the relevant investment theory (Dixit & Pindyck, 1994; Fernandes et al., 2011; de Neufville & Scholtes, 2011), and the economically optimal timing of retrofit investments has been studied for buildings (Kumbaroğlu & Madlener, 2012); the energy-efficiency gap literature explains why cost-effective conversions are nevertheless not made (Jaffe & Stavins, 1994; Allcott & Greenstone, 2012; Gillingham & Palmer, 2014).

Data-driven network analytics and interpretable models

District heating has a data-driven literature of its own: load prediction from weather and calendar data (Dotzauer, 2002; Idowu et al., 2016), fault detection in substations (Gadd & Werner, 2015; Månsson et al., 2019), modelling and optimisation of networks (Talebi et al., 2016; Guelpa et al., 2016; Allegrini et al., 2015) and thermo-hydraulic pipe models for dynamic simulation (van der Heijde et al., 2017). Building-side analytics supply inverse models of consumption and measurement and verification under ASHRAE Guideline 14 (Amasyali & El-Gohary, 2018; Bourdeau et al., 2019; ASHRAE, 2014; Granderson et al., 2016), heat metering has its standard (CEN, 2022), and metamodels of simulation models allow fast exploration (Van Gelder et al., 2014; Westermann & Evins, 2019). The management-science literature adds the requirements that the analysis be prescriptive rather than merely predictive (Bertsimas & Kallus, 2020; Elmachtoub & Grigas, 2022; Ban & Rudin, 2019), that aleatoric uncertainty (future prices, weather) be distinguished from epistemic uncertainty (losses, ages, costs) because only the second can be bought down (Hüllermeier & Waegeman, 2021; Kendall & Gal, 2017), that risk be identified, analysed, treated and recorded (ISO, 2018) and communicated as probabilities and ranges (Spiegelhalter, 2017), that high-stakes recommendations rest on inspectable models (Rudin, 2019; Lipton, 2018; Doshi-Velez & Kim, 2017), with importance, partial dependence and shallow trees making flexible models readable (Lundberg & Lee, 2017; Lundberg et al., 2020; Fisher et al., 2019; Breiman, 2001; Molnar, 2025; Lou et al., 2012; Caruana et al., 2015), and that human judgement be supported rather than replaced (Amershi et al., 2019; Shneiderman, 2020; Fildes et al., 2009). Analytics capability pays through organisational routines (Gunasekaran et al., 2017; Fosso Wamba et al., 2017; Dubey et al., 2020; Brynjolfsson et al., 2021), and poor data quality costs fall on those routines (Haug et al., 2011; Hazen et al., 2014).

Requirements and the framework

Table 2 organises the literature into nine strands and the gap each leaves. Six requirements follow. R1, measured losses: the distribution loss, trap condition and condensate return of the existing system must be estimated from the campus's own plant and building data, because they are the benefit of conversion and they vary by a factor of two or more between campuses. R2, assets as data: the age, condition and renewal timing of the mains must enter the comparison, because conversion avoids renewal and the counterfactual of keeping steam is not free. R3, uncertainty propagated: losses, costs, staffing, prices, discount rate and asset lives must enter as distributions with epistemic and aleatoric components distinguished, and the output must be a probability and a range. R4, phasing as a decision: the order and duration of conversion, the parallel operation of two networks and the retirement date of the steam plant must be modelled, because they change the answer by more than many physical parameters. R5, decision outputs: probability of least cost, break-even gas price and pipe cost, value of information, emissions and abatement cost, so that the decision can be to keep steam with a programme, to convert fast or phased, to add heat pumps, or to measure first. R6, feedback: metered performance of delivered phases must return to the model so that later phases are better estimated. From these, the framework (Figure 1) is designed as a pipeline with four lanes: data sources (plant data, building meters, asset register, climate and loads, costs and policy), physical and reliability models (calibrated loss model, network model, trap and condensate balance, failure hazard), probabilistic economics (life-cycle cost, Monte Carlo, phasing, outputs and sensitivity) and decision and monitoring (screening rule, decision, measurement and verification, governance record), with feedback from verification to the loss model and from sensitivity to the data lane. Figure 2 shows the two systems with their loss flows and the parallel operation that phasing entails; the Methods give their models.

Table 1: Documented campus steam-to-hot-water conversions: what the primary sources state, and the assessment of claims in the motivating draft

Institution / claim	What the primary sources state (quoted or closely paraphrased)	Source	Assessment
Stanford University (SESI)	Conversion of 155 buildings to receive hot water instead of steam; 22 miles of hot-water pipe; in 2015 'anticipated to reduce campus emissions approximately 68%' and 'a net additional $100 million capital investment projected to yield $420 million in savings over the next 35 years'; later reported as 'reduced ... greenhouse gas emissions by 68%' and, by 2025, 80%	Stanford University (2015, 2025); Stanford University (n.d.-b); Xia (2019)	Supported with corrections: 155 buildings (not 150); 68% and $420M were 2015 projections, later reported as achieved (Xia, 2019, gives $425M); the plant is a heat-recovery system, not a boiler swap
University of British Columbia (ADES)	'The conversion will reduce Vancouver campus energy use by 24 per cent and its greenhouse gas emissions by 22 per cent' (2011 projection); $85–88M budget; nine phases 2011–2017; 14 km of 90-year-old steam piping replaced; now 'more than 160 buildings'; 'improves energy efficiency by greater than 24 per cent'	UBC (2011a, 2011b, n.d.-a, n.d.-b, n.d.-c)	Partly supported: 24% energy (projection, later stated as achieved); building counts 100+/130+/160+ by date — '115' appears in no source
Cornell University	'About 19% of all energy entering the distribution system is lost between the central plant and the served buildings'; 'net losses are in the range 15–20% overall'; literature range '8–40% (steam)' and '1–10% (water)'; 2025: about 20% loss to fall to about 5%; conversion 20% complete; steam distribution O&M about $1M/yr	Cornell University (2016, 2025)	Primary source for the order of magnitude of campus steam losses; hot-water figure is a projection
Princeton University	'MEP systems in over 180 buildings will be converted from steam to hot water'; 13 miles of new hot-water piping; 'at least 30% of the heat made in the cogeneration plant is lost in the ground'	Princeton University (n.d.)	In progress; loss figure is the institution's own estimate
Dartmouth College	Low-temperature hot water 'estimated to be 20% more efficient than the current steam system'; designs for 'more than 100 buildings'; combined programme 'could reduce 2010-level greenhouse gas emissions by as much as 84%'	Dartmouth College (2020)	Projections at design stage
Wesleyan University	'Wesleyan's district steam heating system is about 55% efficient'; conversion 'increases distribution efficiency by over 25%'; converted buildings 'are 30 percent more efficient'; 'the current hot water system is 75% efficient ... will increase to 90+% when the conversion is completed in 2029'; 57% of campus converted by 2024	Wesleyan University (2022, 2024a, 2024b)	Supported in substance; the draft's '25–30% energy reduction' appears only in a student newspaper (The Wesleyan Argus, 2020) as a projection
University of Rochester	Hot-water distribution installed with a 2005 cogeneration project ($50M); '22 campus buildings still need to be connected'; '$20 million estimated in building HVAC hot water conversions needed'	University of Rochester (2018)	Documents the long tail of building-side conversion
Michigan Technological University (draft claim: 'feasibility study, 20–30% fuel savings')	Steam plant in operation ('our boilers are 55–75 years old'; 'our best steam boiler is about 86% efficient'); design standard for new buildings: 'steam radiation systems are not permitted'	Michigan Technological University (n.d.-a, n.d.-b)	Not found: no feasibility study or 20–30% figure located
Draft claim: 'FEMP (2018): 15–30% of traps malfunction at any time'	'In steam systems that have not been maintained for 3 to 5 years, between 15% to 30% of the installed steam traps may have failed'; with a maintenance programme 'leaking traps should account for less than 5% of the trap population'; FEMP alert: 'approximately 20% of the steam leaving a central boiler plant is lost via leaking traps' in unmanaged systems	U.S. DOE (2012b); U.S. DOE FEMP (n.d.)	Figure real; attribution and 'at any time' corrected: it applies to systems unmaintained for 3–5 years
Draft claim: 'steam distribution loses 15–25% (DOE, 2022)'; 'hydronic < 5–8%'	No DOE document stating 15–25% was found; Cornell's 19%/15–20% and 'industry 8–40%' support the order of magnitude. Hot-water networks: about 5% projected for campus loops (Cornell); 8–9% in Finland; '8–15%' in western and northern Europe; medians below 20% in IEA countries	Cornell University (2016, 2025); Finnish Energy (n.d.); Smart Cities Marketplace (2023); Nussbaumer & Thalmann (2014)	Order of magnitude supported, attribution not; '< 5–8%' is too low for district heating generally

Table 2: Literature strands, what they establish, representative sources and the gap addressed

Strand	What the literature establishes	Representative sources	Gap addressed here
District heating generations and economics	Fourth-generation district heating lowers supply temperatures (≤ 70 °C) to cut losses and admit heat pumps and waste heat; heat density and pipe design drive distribution cost; return temperatures and substation faults matter	Lund et al. (2014, 2018, 2021); Werner (2017); Frederiksen & Werner (2013); Averfalk & Werner (2020); Persson & Werner (2011); Nussbaumer & Thalmann (2016); Gadd & Werner (2014, 2015)	Campus-scale transition from steam, with the conversion itself as the decision
Steam systems, traps, condensate, boilers	Tip sheets and sourcebooks on trap failure, insulation, condensate return and blowdown; survey methods; condensing boilers and part-load behaviour; water-chemistry handbooks	U.S. DOE (2012a–e); Harrell (2002); Einstein et al. (2001); Sullivan et al. (2010); Che et al. (2004); Lazzarin (2012, 2014); Kemmer (1988); Spirax-Sarco (2007); ASHRAE (2013, 2020)	Loss components assembled into one balance and propagated to economics under uncertainty
Documented campus conversions	Institutional reports of steam-to-hot-water programmes (Stanford, UBC, Cornell, Princeton, Dartmouth, Wesleyan, Rochester, Smith) with projected or reported energy, emission and cost figures	Stanford University (2015, 2025); UBC (2011a, 2011b); Cornell University (2016, 2025); Princeton University (n.d.); Dartmouth College (2020); Wesleyan University (2024a, 2024b)	Figures verified against primary pages (Table 1) and used to bound the model, not as data
Campus and higher-education energy	Energy use characteristics and benchmarking of university buildings; coincidence of loads across a campus; calendar effects; institutional emissions	Khoshbakht et al. (2018); Guan et al. (2016); Chung & Rhee (2014); Gui et al. (2021); Sinha et al. (2010); Sesana et al. (2016); Fonseca & Schlueter (2015)	Synthetic campus with building types, loads and a network
Heat pumps and electrification of district heat	Large heat pumps and heat-recovery in district heating; placement and operation; high-temperature heat pumps; power-to-heat; the Stanford heat-recovery experiment	Østergaard & Andersen (2016); Sayegh et al. (2018); David et al. (2017); Lund & Persson (2016); Pieper et al. (2018); Arpagaus et al. (2018); Bloess et al. (2018); de Chalendar et al. (2019)	Heat-pump option modelled as enabled by low-temperature hot water
Reliability, maintenance and asset management	Age-dependent failure (Weibull), preventive-maintenance optimisation, condition-based maintenance; risk management of district heating networks; resilience	Weibull (1951); Barlow & Hunter (1960); Dekker (1996); Jardine et al. (2006); Sernhed & Jönsson (2017); Sharifi & Yamagata (2016); National Board (2025)	Failure hazard, renewal timing and trap survey/monitoring economics inside the LCC
Life-cycle costing, uncertainty and decision analysis	NIST/ASTM/ISO procedures; probabilistic LCC; Sobol sensitivity; value of information; real options and flexibility in phased investment	Kneifel & Webb (2020); ASTM International (2017); ISO (2017); Di Giuseppe et al. (2017); Sobol' (2001); Saltelli et al. (2010); Howard (1966); Dixit & Pindyck (1994); de Neufville & Scholtes (2011)	Monte Carlo LCC with EVPI, break-even values and a phasing analysis
Data-driven building and network analytics	Load forecasting and fault detection in district heating; inverse models and M&V; network simulation tools; thermo-hydraulic pipe models; heat-loss models of buried pipes	Dotzauer (2002); Idowu et al. (2016); Gadd & Werner (2015); Månsson et al. (2019); ASHRAE (2014); Allegrini et al. (2015); van der Heijde et al. (2017); Bøhm (2000); Danielewicz et al. (2016)	Calibrated loss model, metering experiment and monitoring economics as the framework's data lane
Decision analytics and interpretable models	Prescriptive analytics; aleatoric vs epistemic uncertainty; risk communication; interpretable models; human–AI interaction; analytics capability and data quality	Bertsimas & Kallus (2020); Hüllermeier & Waegeman (2021); Spiegelhalter (2017); Rudin (2019); Amershi et al. (2019); Mikalef et al. (2019); Hazen et al. (2014)	Metamodel targets the decision; shallow tree as a readable rule; provenance and governance

Figure 1: Data-driven decision-analytics pipeline for campus heating conversion: data sources, physical and reliability models, probabilistic economics, decision and monitoring, with feedback loops

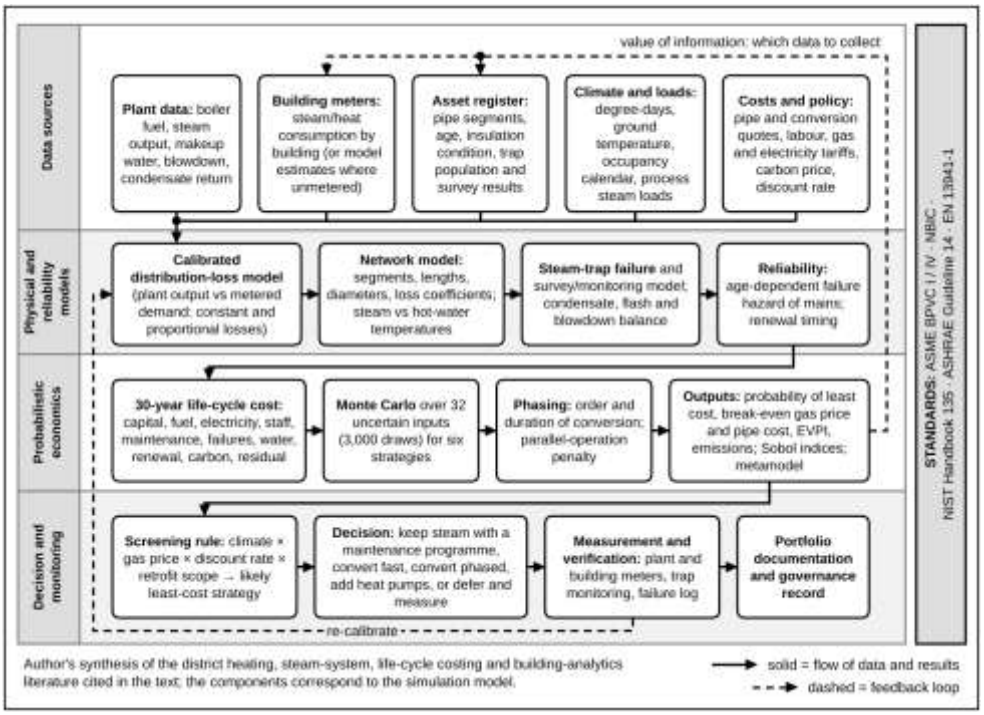
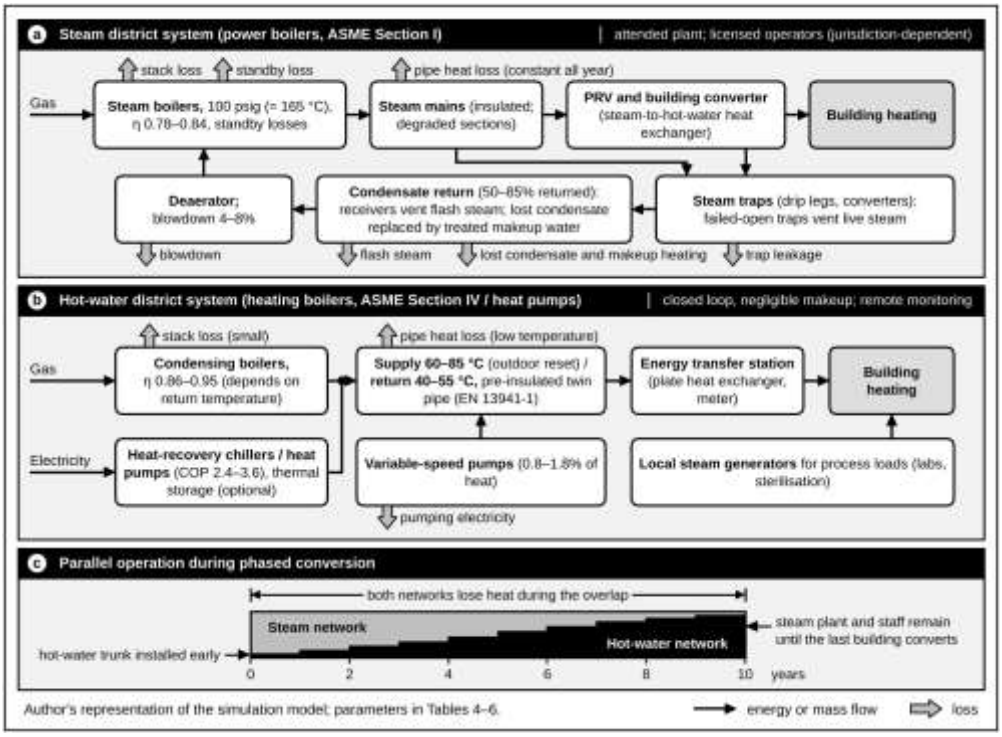


Figure 2: Steam and hot-water campus heating systems with their losses, and parallel operation during phased conversion



Three design choices distinguish the framework from a conventional feasibility study. It treats the existing steam system's losses and asset condition as quantities to be measured and bounded rather than quoted, so that the benefit of conversion is a distribution with a provenance. It treats phasing as part of the decision rather than as a delivery detail, so that the cost of parallel operation is visible. And

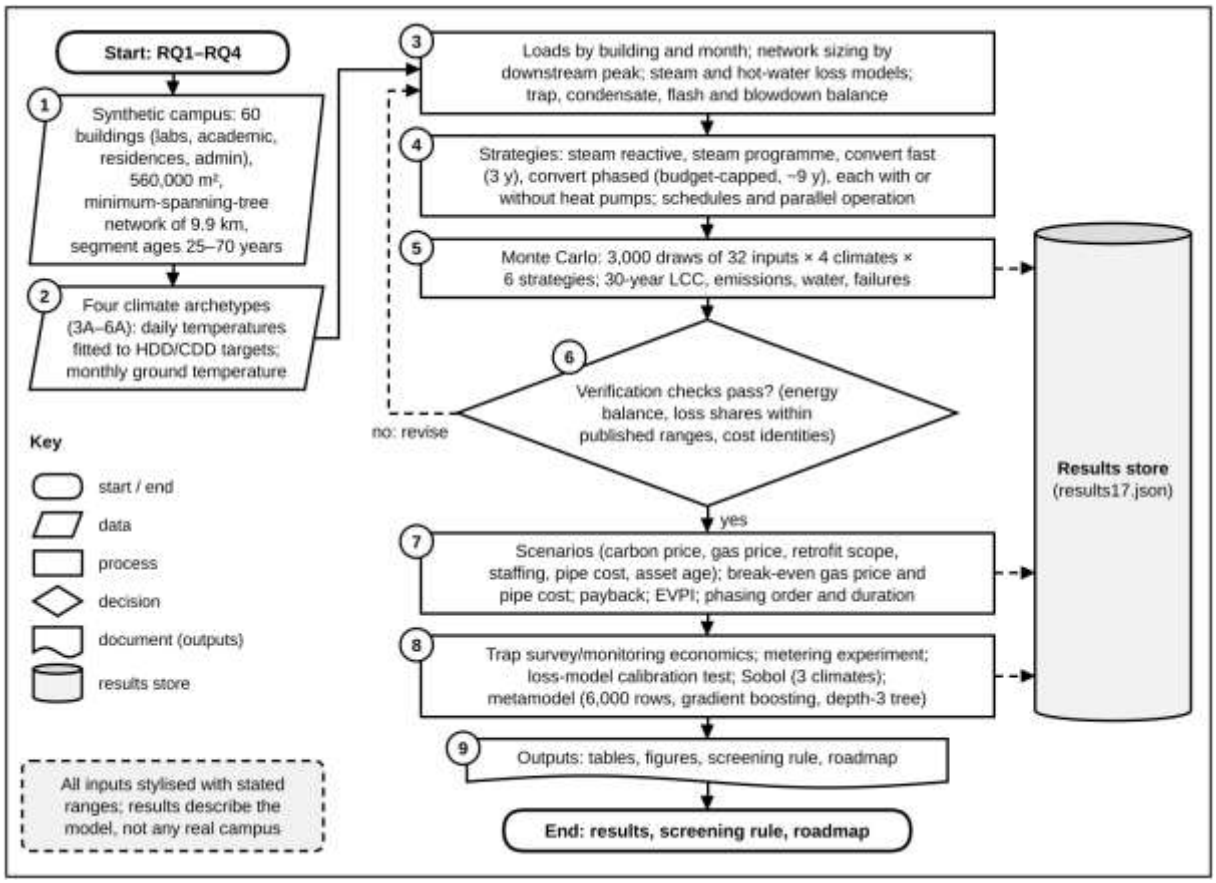
it produces probabilities, break-even values and a value of information rather than a payback period, so that "measure first" is an option with a price. The evaluation that follows tests whether these outputs are informative on a model whose truth is known.

Methods

Study design

The study follows the design-science process — problem and requirements, design of the artefact, evaluation, communication (Peffers et al., 2007; Hevner et al., 2004) — with an artificial evaluation on a parametric model, chosen because the framework's outputs (probabilities, break-even values, value of information, the cost of phasing) can only be checked against a model whose inputs are known (Venable et al., 2016; Sonnenberg & vom Brocke, 2012). Figure 3 shows the design as a flowchart: a synthetic campus and four climate archetypes, loads and network sizing, steam and hot-water loss models, six strategies with their schedules, Monte Carlo life-cycle costing, verification, scenarios and break-even analysis, the data-lane experiments (trap economics, metering, calibration), Sobol sensitivity and a metamodel, and outputs. The simulation follows the conventions of simulation studies — explicit assumptions, verification of each component, common random numbers across alternatives (Law, 2015; Sargent, 2013) — and of life-cycle costing under the NIST handbook (Kneifel & Webb, 2020). It is implemented in Python with NumPy, SciPy, pandas, scikit-learn, LightGBM and SALib (Harris et al., 2020; Virtanen et al., 2020; Pedregosa et al., 2011; Ke et al., 2017; Herman & Usher, 2017), runs in about a minute and a half, and writes a results file from which every table and figure is produced. No measured data from any campus, utility or supplier were used; the documented conversions of Table 1 bound the model's loss shares and delivered efficiencies but do not enter it as data.

Figure 3: Study design as a flowchart: synthetic campus and climates, loads and loss models, strategies and schedules, Monte Carlo life-cycle costing over 4 climates × 6 strategies, verification, scenarios, data-lane experiments, sensitivity and metamodel, outputs



Synthetic campus, network and climate archetypes

Table 3 lists the archetypes and Figure 4 shows them. The campus has 60 buildings of four types — 12 laboratories, 24 academic buildings, 16 residences and 8 administrative buildings — with log-normally distributed floor areas (means 5,800–11,600 m² by type, total 560,573 m²) placed at random on a 1.6 km × 1.2 km site with the plant at its western edge. Heat demand per building is space heating proportional to monthly heating degree-days at 0.030–0.055 kWh per m² and degree-day by type, domestic hot water of 3–25 kWh per m² per year (residences highest, reduced in summer) and process steam of 14 kWh per m² per year in laboratories and 2 in residences, in the ranges of the higher-education benchmarks (Khoshbakht et al., 2018; Chung & Rhee, 2014; Guan et al., 2016). The network is the minimum spanning tree connecting the plant and the buildings, with Manhattan routing (lengths × 1.25), giving 60 segments and 9,897 m of trench; each segment serves the buildings downstream of it, is sized to their diversified peak (DN50 to DN250) and carries an age drawn around 64 years less 1.2 years per tree depth (range 13–85, mean 48, with 3.3 km older than 55 years) and a degraded-insulation share that rises with age (2–39% of length), standing in for an asset register. Four climate archetypes span ASHRAE Standard 169 zones 3A to 6A, with heating degree-day targets of 1,500, 2,500, 3,400 and 4,300 °C-days (base 18 °C) (ASHRAE, 2021b); a daily temperature series is generated for each as an annual cosine plus first-order autoregressive noise with its mean and amplitude fitted to the degree-day targets, and the ground temperature at pipe depth is the annual mean plus 1.5 °C with a damped, lagged seasonal cycle (Day, 2006; Bøhm, 2000). Campus demand runs from 39.5 GWh per year (70 kWh/m²) in 3A to 99.8 GWh (178 kWh/m²) in 6A, with diversified peaks of 16.6–28.4 MW and linear heat densities of 4.0–10.1 MWh per metre of trench, in the range where district heating is competitive (Persson & Werner, 2011).

Figure 4: Synthetic campus and climate archetypes: (a) network with building types, areas and segment ages, (b) monthly campus heat demand by climate, (c) segment age and insulation condition, (d) daily temperature distributions

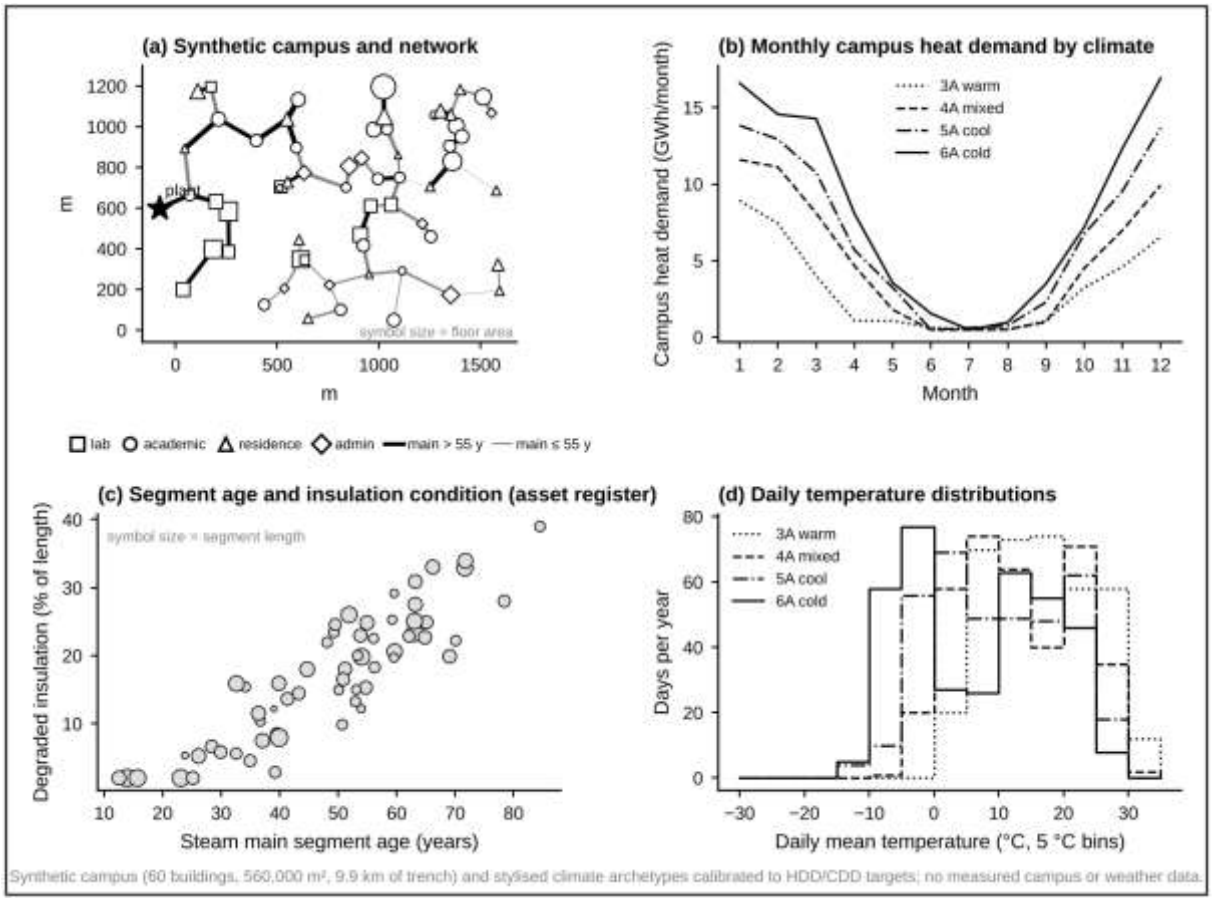


Table 3: Campus archetype (building types, areas, loads, schedules), network (segments, ages, condition) and climate archetypes (degree-days, temperatures, demand, peak, heat density)

Element	Count / degree-days	Area (m²) / temperatures	Space heating (kWh/m² ·HDD) / demand	DHW (kWh/m² yr) / peak	Process steam (kWh/m² yr) / condition	Schedule / basis
Lab	12	11,613 (5,810–20,502)	0.055	5	14	24/7 ventilation-driven
Academic	24	10,466 (3,259–35,096)	0.035	4	0	academic calendar
Residence	16	7,744 (3,248–18,071)	0.030	25	2	year-round, lower in summer
Admin	8	5,767 (2,842–9,911)	0.030	3	0	academic calendar
Network	60 segments	trench 9,897 m; 3,309 m older than 55 y	DN50–DN250 by downstream peak	ages 13–85 y (mean 48)	degraded insulation 2–39% of length	minimum spanning tree from the plant; traps 1 per 40 m plus 3 per building
3A warm-humid	HDD18 1500 / CDD18 1000	mean air 17.3 °C; ground 15.2–22.5 °C	demand 39.5 GWh/yr (70 kWh/m²)	peak 16.6 MW	heat density 4.0 MWh per m of trench	daily temperatures fitted to degree-day targets
4A mixed-humid	HDD18 2500 / CDD18 650	mean air 13.2 °C; ground 10.2–19.3 °C	demand 61.0 GWh/yr (109 kWh/m²)	peak 22.8 MW	heat density 6.2 MWh per m of trench	daily temperatures fitted to degree-day targets
5A cool-humid	HDD18 3400 / CDD18 450	mean air 10.5 °C; ground 7.6–16.5 °C	demand 80.4 GWh/yr (143 kWh/m²)	peak 27.5 MW	heat density 8.1 MWh per m of trench	daily temperatures fitted to degree-day targets
6A cold	HDD18 4300 / CDD18 300	mean air 7.0 °C; ground 3.1–14.0 °C	demand 99.8 GWh/yr (178 kWh/m²)	peak 28.4 MW	heat density 10.1 MWh per m of trench	daily temperatures fitted to degree-day targets

Steam system model

Table 4 gives the steam model. Steam is generated at about 100 psig (165 °C saturation) with enthalpy 2,770 kJ/kg; it delivers 2,260 kJ/kg at the building converter after pressure reduction, and the condensate returns at 90 °C. Boiler duty per kilogram is the difference between steam enthalpy and feedwater enthalpy, where feedwater mixes returned condensate (fraction r of the mass, at 90 °C plus a recovered share of flash) with cold makeup at 12 °C; receivers vent the remaining flash, and blowdown of 6% of feedwater with 50% heat recovery adds to the duty (U.S. DOE, 2012d; U.S. DOE, 2012e; Spirax-Sarco, 2007). The boiler's full-load efficiency of 0.78–0.84 (HHV) is reduced at part load and in summer standby by a factor $1 - 0.18(1 - \mathrm{LF})^2$, where LF is the monthly load factor relative to the peak month, representing cycling and standby losses of a plant kept pressurised all year for hot water and process loads (Harrell, 2002; ASHRAE, 2020). Distribution heat loss is the sum over live segments of length × U × (165 − T_ground) for the supply and length × U_c × (90 − T_ground) for the condensate return, over the hours of each month, with U of 0.35–0.95 W/m·K and U_c of 0.22–0.57 by nominal diameter for sound insulation, multiplied by 3 on the degraded share of each segment; both coefficients and the degraded share carry draw-level scale factors (U.S. DOE, 2012c; ASTM International, 2019; Danielewicz et al., 2016). The trap population is one per 40 m of main plus three per building; under reactive maintenance a share f of 0.12–0.30 is failed open, under a programme 0.04, and each failed trap vents 10 kg/h of steam at 0.61 kWh/kg, a stylised rate in the range of the published orifice tables (U.S. DOE, 2012b; U.S. DOE FEMP, n.d.). The converter loses 1.5% at the building. Makeup water is the unreturned condensate plus blowdown, priced at 6 per m³ including treatment (Kemmer, 1988). Staffing is an attended plant of 4.5–6.5 FTE at a loaded wage of 80–130 thousand while any building remains on steam, which represents the operator rules for high-pressure boilers in many jurisdictions and is varied in a scenario (ASME, 2025a; National Board, n.d.); materials are 0.9% per year of half the

renewal value of live mains, trap replacements 300 each at a failure rate of 0.10 per trap-year, and the programme costs 1.0 million of capital (insulation repair halving the degraded share, trap replacement) plus 120 thousand per year and two surveys per trap-year (Sullivan et al., 2010). Reliability uses a Weibull hazard with shape 2.6 and scale 65 years scaled by a factor of 1.5–4.0 and multiplied by live length, each failure costing 30–120 thousand in repair and outage (Weibull, 1951; Dekker, 1996; Sernhed & Jönsson, 2017); segments are renewed when they reach an age of 55–70 years at 2,000–4,500 per metre of trench unless they are to be decommissioned within five years, and the steam boilers are replaced in year 12 at 300–450 per kW if steam continues for five or more years beyond it (life-extension repairs at 20% of that otherwise).

Table 4: Steam system model: generation, mains and condensate return, traps, condensate and makeup, building side, staffing and maintenance, reliability and renewal

Element	Model	Baseline values and uncertainty	Basis
Steam generation	Boiler duty = steam mass × (h_g − h_feed) with feedwater enthalpy from returned condensate (90 °C, plus recovered flash) and makeup (12 °C); blowdown 6% of feedwater with 50% heat recovery; efficiency η × (1 − 0.18 × (1 − LF)²) with monthly load factor LF	h_g 2770 kJ/kg at ≈100 psig; η 0.78–0.84 (HHV)	U.S. DOE (2012a, 2012e); Harrell (2002); ASHRAE (2020)
Steam mains and condensate return	Heat loss = Σ L × U × (T − T_ground) × hours, supply at 165 °C all year, return at 90 °C; degraded-insulation share per segment rising with age, multiplier 3 on affected length	U 0.35–0.95 W/m·K (supply), 0.22–0.57 (return) by DN; scale 0.8–1.3; degraded share scale 0.6–1.4	U.S. DOE (2012c); ASTM International (2019); Bøhm (2000); Danielewicz et al. (2016)
Steam traps	Population = trench/40 m + 3 per building; failed-open share f under reactive maintenance, 0.04 under a programme; each failed trap vents 10 kg/h at 0.61 kWh/kg	f 0.12–0.30 (reactive); programme 0.04	U.S. DOE (2012b); U.S. DOE FEMP (n.d.); Einstein et al. (2001)
Condensate, flash and makeup	Returned fraction r; receivers vent flash unless recovered (20%); unreturned condensate replaced by treated makeup; water priced per m³ including treatment	r 0.50–0.85; water 6 per m³	U.S. DOE (2012d); Kemmer (1988); Spirax-Sarco (2007)
Building side	Steam-to-hot-water converter loss 1.5%; process steam loads (labs, residences) served by the network	–	ASHRAE (2013, 2020)
Staffing and maintenance	Attended high-pressure plant: FTE × loaded wage while any building is on steam; materials 0.9% of half the renewal value of active mains; trap replacements at 300 each; programme: 1.0 M capital, 120 k/yr plus two surveys per trap-year	FTE 4.5–6.5; wage 80–130 k	ASME (2025a); National Board (n.d.); Sullivan et al. (2010)
Reliability and renewal	Failures per km-year = c × (2.6/65)(age/65)^1.6 (Weibull hazard); cost per failure includes repair and outage; segments renewed at age 55–70 at 2,000–4,500 per m unless decommissioned within five years; boiler replacement in year 12 if steam continues	c 1.5–4.0; failure cost 30–120 k	Weibull (1951); Dekker (1996); Sernhed & Jönsson (2017)

Hot-water system, strategies and schedules

Table 5 gives the hot-water model and the strategies. Condensing boilers have an efficiency of 0.90–0.95 at full condensing, reduced by up to 0.07 as the return temperature rises from 42 to 55 °C (Che et al., 2004; Lazzarin, 2012); the plant is sized to 1.3 times the campus peak at 200–350 per kW, half installed at the start of the programme and half at completion. The network is pre-insulated twin pipe with supply temperature reset between 60 and 85 °C against outdoor temperature and a return of 40–55 °C, losing length × U_h × (T_mean − T_ground) with U_h of 0.18–0.45 W/m·K for the pair by diameter, and pumping electricity of 0.8–1.8% of heat delivered (CEN, 2019; Dalla Rosa et al., 2011; Europump & Hydraulic Institute, 2004). Each building receives an energy transfer station with a plate heat exchanger and meter (60–150 thousand, 0.5% loss, 900 per year maintenance) (CEN, 2022; UBC, 2011b); a share of 0.3–0.7 of buildings needs internal terminal-unit retrofits at 40–100 per m², which is the most uncertain conversion cost and the one that the Rochester status report documents as the long tail of a programme (University of Rochester, 2018); laboratories and, at half weight, residences receive local gas steam generators for process loads at 220 thousand each, burning gas at an effective efficiency of 0.76. The heat-pump option adds a heat-recovery and heat-pump plant sized to 45% of peak at 900–

1,400 per kW including storage, supplying 40–70% of annual hot-water heat at a seasonal COP of 2.4–3.6 from the year after conversion completes, with the boilers covering the rest (de Chalendar et al., 2019a; Østergaard & Andersen, 2016; Arpagaus et al., 2018). Decommissioning costs 100 per metre of steam main and 2.0 million for the plant; residual values are straight-line on pipe (50 years), boilers (25), heat pumps (20), transfer stations (25) and renewed steam mains (50).

Six strategies are compared. STEAM-REACTIVE keeps steam with reactive maintenance; STEAM-PROGRAMME keeps steam with the trap-and-insulation programme; CONVERT-FAST converts all buildings in three equal annual batches in plant-outward order; CONVERT-PHASED converts in benefit-cost order — branch heat loss weighted by age, divided by the building's conversion cost including pipe — under an annual capital cap of 11% of the total conversion cost, which completes in nine years; and CONVERT-FAST-HP and CONVERT-PHASED-HP add the heat-pump plant in the year after completion. Alternative orderings (oldest mains first, plant outward, random) under the same cap and programme durations of 3, 6, 10 and 15 years are evaluated as a phasing experiment (Kumbaroğlu & Madlener, 2012; de Neufville & Scholtes, 2011). Parallel operation follows from the schedule: a steam segment stays live until the last building downstream of it converts, hot-water pipe on a segment is installed when the first building downstream converts, a building converted in a year is served by hot water from the next, and the steam plant with its staff, standby losses and trap population remains until the last building converts.

Table 5: Hot-water system model, heat-pump option, conversion strategies, schedules, parallel operation, decommissioning and residual value

Element	Model	Baseline values and uncertainty	Basis
Hot-water generation	Condensing boilers: η = η_full − 0.07 × clip((T_return − 42)/13, 0, 1); plant sized to 1.3 × campus peak, half installed at the start and half at completion	η_full 0.90–0.95; T_return 40–55 °C; 200–350 per kW	Che et al. (2004); Lazzarin (2012, 2014); ASME (2025b)
Hot-water network	Pre-insulated twin pipe; supply 60–85 °C by outdoor reset, loss = Σ L × U × (T_avg − T_ground) × hours; variable-speed pumping as a share of heat delivered; closed loop	U 0.18–0.45 W/m·K (pair) by DN; scale 0.8–1.3; pumping 0.8–1.8%	CEN (2019); Dalla Rosa et al. (2011); Li & Svendsen (2012); Europump & Hydraulic Institute (2004)
Energy transfer stations and buildings	Plate heat exchanger and meter per building (0.5% loss); internal terminal-unit retrofit for a share of buildings; local gas steam generators for process loads (η 0.76 incl. losses)	ETS 60–150 k; retrofit share 0.3–0.7 at 40–100 per m²; generators 220 k per lab	UBC (2011b); University of Rochester (2018); CEN (2022)
Heat-pump option	Heat-recovery chillers / heat pumps supply a share of annual hot-water heat at a seasonal COP; capacity 45% of peak; added in the year after conversion completes	share 0.4–0.7; COP 2.4–3.6; 900–1,400 per kW	de Chalendar et al. (2019); Østergaard & Andersen (2016); Arpagaus et al. (2018)
Conversion schedules	Fast: plant-outward order in 3 equal annual batches. Phased: benefit-cost order (branch loss × age / cost) under an annual capital cap of 11% of total conversion cost (≈ 9 years); alternatives: oldest-first, plant-outward, random; durations 3/6/10/15 years	–	Kumbaroğlu & Madlener (2012); de Neufville & Scholtes (2011)
Parallel operation	A steam segment stays live until the last downstream building converts; hot-water pipe is installed when the first downstream building converts; steam plant and staff remain until the last building converts; both networks lose heat during the overlap	–	Author's model; Cornell University (2025); Wesleyan University (2024a)
Decommissioning and residual value	100 per m of steam main and 2 M for the plant at completion; straight-line residual value of pipe (50 y), boilers (25), heat pumps (20), ETS (25) and renewed steam mains (50) at the horizon	–	Kneifel & Webb (2020)

Uncertain inputs, life-cycle cost and decision metrics

Table 6 lists the 32 uncertain inputs with their distributions — demand scale, insulation condition, loss coefficients, trap failure share, condensate return, boiler efficiencies, return temperature, pumping, all unit costs, renewal age, failure scale and cost, staffing and wages, gas and electricity prices and escalation, discount rate, grid carbon intensity and its decline, and the heat-pump parameters — with ranges from the sources in Tables 4–5 and, for prices, in the ranges of recent commercial tariffs and the

NIST escalation projections (EIA, 2023; Kneifel & Lavappa, 2023); the real discount rate is 2–6% with mode 3% (Kneifel & Webb, 2020). Table 7 summarises the methods. The 30-year life-cycle cost of each strategy is the present value of capital, steam renewal and boiler replacement, gas, electricity, staff, maintenance, failures, water and carbon, less the discounted residual value (Kneifel & Webb, 2020; ASTM International, 2017; ISO, 2017).

Table 6: The 32 uncertain inputs sampled in the Monte Carlo analysis

Input	Description	Distribution	Range (min – mode – max or min – max)
load_f	Scale on building heat demand (calibration uncertainty)	triangular	0.85 – 1 – 1.15
ins_deg	Scale on the degraded-insulation share of steam mains	uniform	0.6 – 1.4
u_steam_f	Scale on steam and condensate pipe heat-loss coefficients	uniform	0.8 – 1.3
u_hw_f	Scale on hot-water pipe heat-loss coefficients	uniform	0.8 – 1.3
f_fail	Failed-open steam trap share under reactive maintenance	uniform	0.12 – 0.3
r_cond	Condensate return fraction	uniform	0.5 – 0.85
eta_steam	Steam boiler full-load efficiency (HHV)	uniform	0.78 – 0.84
eta_hw	Hot-water boiler efficiency at full condensing (HHV)	uniform	0.9 – 0.95
t_ret	Hot-water return temperature (°C)	uniform	40 – 55
pump_frac	Hot-water distribution pumping electricity as a share of heat delivered	uniform	0.008 – 0.018
pipe_cost	Installed hot-water pipe cost per metre of trench (DN150 basis)	triangular	1200 – 1700 – 2600
ets_cost	Energy transfer station cost per building	triangular	60000 – 90000 – 150000
int_share	Share of buildings needing internal terminal-unit retrofit	uniform	0.3 – 0.7
int_cost	Internal retrofit cost per m² of affected buildings	triangular	40 – 60 – 100
hwb_cost	Hot-water boiler plant cost per kW	triangular	200 – 260 – 350
sb_cost	Steam boiler replacement cost per kW	triangular	300 – 380 – 450
renewal_cost	Steam main renewal cost per metre of trench	triangular	2000 – 2800 – 4500
renew_age	Age at which steam mains are renewed (years)	uniform	55 – 70
fail_c	Scale on the age-dependent failure rate of steam mains	triangular	1.5 – 2.5 – 4
fail_cost	Cost per distribution failure (repair plus outage)	triangular	30000 – 60000 – 120000
fte_steam	Operating staff for the attended steam plant (FTE)	uniform	4.5 – 6.5
fte_hw	Operating staff for the hot-water plant (FTE)	uniform	1 – 3
wage	Loaded annual cost per FTE	triangular	80000 – 100000 – 130000
p_gas	Gas price per kWh (6–15 per MMBtu)	triangular	0.02 – 0.031 – 0.05
p_elec	Electricity price per kWh	triangular	0.08 – 0.12 – 0.18
esc_gas	Real gas price escalation per year	uniform	−0.01 – 0.025
disc	Real discount rate	triangular	0.02 – 0.03 – 0.06
grid_ci	Grid carbon intensity, year 1 (kg CO_2 e/MWh)	triangular	250 – 400 – 550
grid_decline	Annual decline in grid carbon intensity	uniform	0 – 0.05
hp_cop	Seasonal COP of the heat-recovery/heat-pump plant	uniform	2.4 – 3.6
hp_share	Share of annual hot-water heat supplied by heat pumps	uniform	0.4 – 0.7
hp_cost	Heat pump plant cost per kW thermal, including storage	triangular	900 – 1100 – 1400

For each climate, 3,000 draws of the inputs are evaluated for all six strategies with common draws, so that differences are paired. Outputs are the distribution of each strategy's cost, the probability that each is least-cost, the probability that the conversion family (fast or phased, with or without heat pumps) beats the steam family (reactive or programme), pairwise savings against the steam programme, the expected value of perfect information (Howard, 1966; Morgan & Henrion, 1990), the payback year at which the cumulative discounted cost of phased conversion falls below the steam programme's, thirty-year emissions with gas at 181 kg CO_2 e per MWh of fuel and a 1.15 upstream factor and electricity at a declining grid intensity (EPA, 2024; Gagnon et al., 2021), and abatement cost. Because the life-cycle cost is linear in the gas price and in the pipe cost for a fixed draw, break-even values at which a conversion strategy equals the steam programme are solved per draw and reported as percentiles. Scenarios fix the carbon price at 51 or 190 per tonne (Rennert et al., 2022; EPA, 2023), the gas price at 15 per MMBtu, the internal-retrofit share at 0.15, the steam staffing at the hot-water level (an unattended

plant), the pipe cost at ±25%, and all segment ages at 20 years younger or 10 years older.

Table 7: Methods: horizon and metric, cases, Monte Carlo, break-even, scenarios, phasing, data-lane experiments, sensitivity, metamodel, verification and software

Element	Setting
Horizon and metric	30-year life-cycle cost in constant prices: capital, steam renewal and boiler replacement, gas, electricity, staff, maintenance, failures, water, carbon (scenarios), less residual value; real discount rate 2–6% (mode 3%)
Cases and strategies	4 climates × 6 strategies (steam reactive, steam programme, convert fast, convert phased, each conversion with heat pumps); one synthetic campus
Monte Carlo	3,000 draws of 32 inputs per climate with common random numbers across strategies; probability of least cost, pairwise savings, EVPI, payback
Break-even	Gas price and hot-water pipe cost at which each conversion strategy equals the steam programme, solved per draw from the linearity of LCC in those inputs
Scenarios	Carbon price 51 and 190 per tonne; pipe cost ±25%; internal retrofit share 0.15; unattended steam plant (steam staff = hot-water staff); gas 15 per MMBtu; all mains 20 years younger or 10 years older; retrofit 0.15 with carbon 51
Phasing	Ordering rules (benefit-cost, oldest-first, plant-outward, random) under the same capital cap; programme durations 3, 6, 10, 15 years; parallel-operation staff cost and peak annual capital
Data-lane experiments	Trap survey interval versus continuous monitoring (closed form checked by simulation); metering experiment (precision of the loss estimate versus metered share, plant-meter accuracy and years of data); loss-model calibration on synthetic monthly data
Sensitivity	Sobol first- and total-order indices of steam-programme minus phased-conversion LCC (and versus the heat-pump variant) for 3A, 4A and 6A; Saltelli sampling, 128 base points (4,352 evaluations per climate)
Metamodel	6,000 rows (1,500 draws × 4 climates); features: the 32 inputs plus heating degree-days; gradient boosting for 'conversion family least-cost', multiclass for the least-cost strategy, regressor for the conversion margin per m²; depth-3 and depth-4 trees; stratified 70/30 split; partial dependence and maps
Verification	Energy balance per kg of steam; distribution loss shares within published ranges (Cornell 15–20%, industry 8–40%); delivered efficiency of steam ≈ 55% and hot water ≈ 88% consistent with institutional figures; cost identities; monotonic responses to scenarios; trap model closed form versus simulation
Software and runtime	Python, NumPy, SciPy, pandas, scikit-learn, LightGBM, SALib; about 1 minutes; results file results17.json

Data-lane experiments: trap economics, metering and calibration

Three experiments represent the data lane of the framework. The trap experiment computes the expected annual cost per trap of surveying at an interval τ — leakage during the mean undetected time λτ/2 at the cost of a failed trap-year, plus the survey cost divided by τ — and of continuous monitoring, which detects a failure in seven days at a sensor cost of 80 per trap-year, for failure rate λ = 0.10 per trap-year, leak 53,400 kWh per failed trap-year, boiler efficiency 0.81 and three gas prices; the closed form, whose optimum is $\tau^* = \sqrt{(2c_s/\lambda c_{leak})}$ in the manner of the classical inspection models (Barlow & Hunter, 1960; Dekker, 1996), is checked against a simulation of 2,000 traps over ten years. The metering experiment estimates the distribution loss as plant output minus building consumption when a share of buildings is metered (±3%) and the rest are estimated from a model (±20% per building), with plant meters of ±2% or ±1% and one or three years of data, reporting the standard error of the estimate as a share of the true loss (20% of demand) over 400 replications. The calibration test regresses twelve months of synthetic plant steam output on metered building demand and operating hours — plant = (1 + k) × demand + constant × hours — with 3% plant and 2% meter noise, and compares the fitted proportional losses (condensate, flash, blowdown, converter) and constant losses (pipe and traps) with the generator's; the constant term is identified by the intercept rather than by a temperature term because steam pipe losses do not follow the weather (ASHRAE, 2014; Granderson et al., 2016). Anomaly screening of consumption series before fitting (Chandola et al., 2009) and blocked cross-validation of calibrated models (Bergmeir & Benítez, 2012) are the controls that would accompany these steps on real

data.

Sensitivity analysis and metamodel

Global sensitivity analysis uses Sobol first- and total-order indices of the difference between the steam-programme and phased-conversion life-cycle costs, and between the steam programme and the phased heat-pump variant, for the 3A, 4A and 6A climates, with Saltelli sampling of 128 base points (4,352 evaluations per climate) (Sobol', 2001; Saltelli et al., 2010; Herman & Usher, 2017; Iwanaga et al., 2022). The metamodel is fitted to 1,500 draws from each climate (6,000 rows) with 33 features — the 32 inputs and heating degree-days — to predict whether the conversion family is least-cost, which strategy is least-cost, and the conversion margin per m², using gradient boosting with a stratified 70/30 split (Ke et al., 2017; Friedman, 2001; Hastie et al., 2009); depth-3 and depth-4 decision trees are fitted to the same target as transparent screening rules (Rudin, 2019; Van Gelder et al., 2014; Westermann & Evins, 2019), and partial dependence on gas price, pipe cost, trap failure share, steam staffing, renewal cost and degree-days, with maps over gas price and pipe cost, are computed from the fitted model (Molnar, 2025). The protocol avoids leakage — features are inputs only, targets are computed from outputs (Kaufman et al., 2012) — reports discrimination as AUC and accuracy against the base rate (Fawcett, 2006), and checks the partial dependence on degree-days against the Monte Carlo probabilities by climate (Guo et al., 2017); comparisons between model classes, which would need corrected resampled tests (Nadeau & Bengio, 2003; Demšar, 2006), are outside the purpose, which is to show that a readable rule can be extracted and how much it loses.

Verification

Verification checks were that the climate series reproduce their degree-day targets, that the per-kilogram steam balance closes (boiler duty equals delivered heat plus condensate, flash, makeup and blowdown losses), that steam distribution losses as a share of plant output (20–35%) lie within the Cornell and industry ranges and that delivered efficiencies (steam about 55%, hot water about 88%) match the institutional figures of Table 1, that the cost components sum to the reported life-cycle costs, that break-even values reproduce equality when substituted back, that responses to the scenario parameters are monotonic, and that the trap model's closed form agrees with its simulation (Sargent, 2013; Law, 2015). The model code is organised so that each component — campus, climate, loss models, schedules, costs — can be replaced independently.

Results

Where the fuel goes (RQ2)

Figure 5 and Table 8 decompose the fuel. In the steam system under reactive maintenance, boiler stack and standby losses take 22–24% of the fuel in every climate, pipe heat loss 8–13%, trap leakage 3–6%, condensate, flash and blowdown 7–8% and the building converters about 1%, so that 49% of the fuel reaches the buildings as heat in the warm climate and 59% in the cold one; distribution losses — pipe, traps and condensate — are 35% of plant output in 3A, 29% in 4A, 26% in 5A and 23% in 6A. The gradient is a density effect: pipe and trap losses are nearly constant through the year because the steam temperature does not follow the weather, so they weigh more where the heat demand is small. The maintenance programme removes most of the trap leakage and half of the degraded-insulation loss, raising delivered efficiency to 54–62% and lowering distribution loss to 20–29% of plant output; it is the cheapest intervention in the study and is cheaper than reactive maintenance in 86–89% of draws, by a mean of 3.5–3.8 per m² over 30 years. The hot-water system in year 30, after conversion, loses 10% of its fuel in the boiler stack and 1–2% in the pipes, delivers 87–88% of fuel as heat, and spends 2.5–6% of its fuel in the local steam generators that serve the laboratories' process loads. Fuel use falls by 32–43% relative to reactive steam and by 29–37% relative to the programme — from 112 to 70 GWh per year in the mixed-humid climate — and makeup water falls from 34,000–73,000 m³ per year to a negligible closed-loop quantity. These shares sit where the documented campuses put them: the steam delivered efficiency of 54% in 4A is Wesleyan's "about 55%" (Wesleyan University, 2024a), the distribution losses of 23–35% bracket Cornell's 19% and Princeton's "at least 30%" (Cornell University, 2016; Princeton University, n.d.), and the hot-water loss of 1–2% is at the optimistic end of Cornell's projected 1–4% (Cornell University, 2016).

Figure 5: Fuel decomposition and efficiency: (a) where the fuel goes under steam (reactive, programme) and hot water, (b) delivered efficiency and distribution loss by climate, (c) steam loss components under uncertainty, (d) steam-system water use

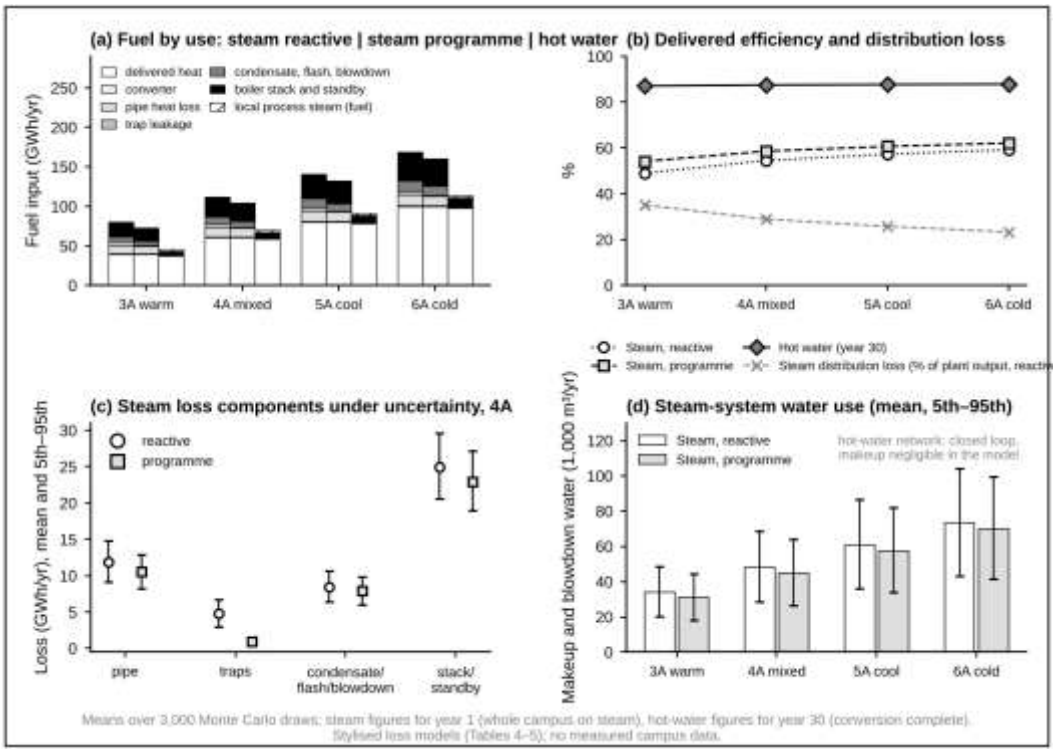


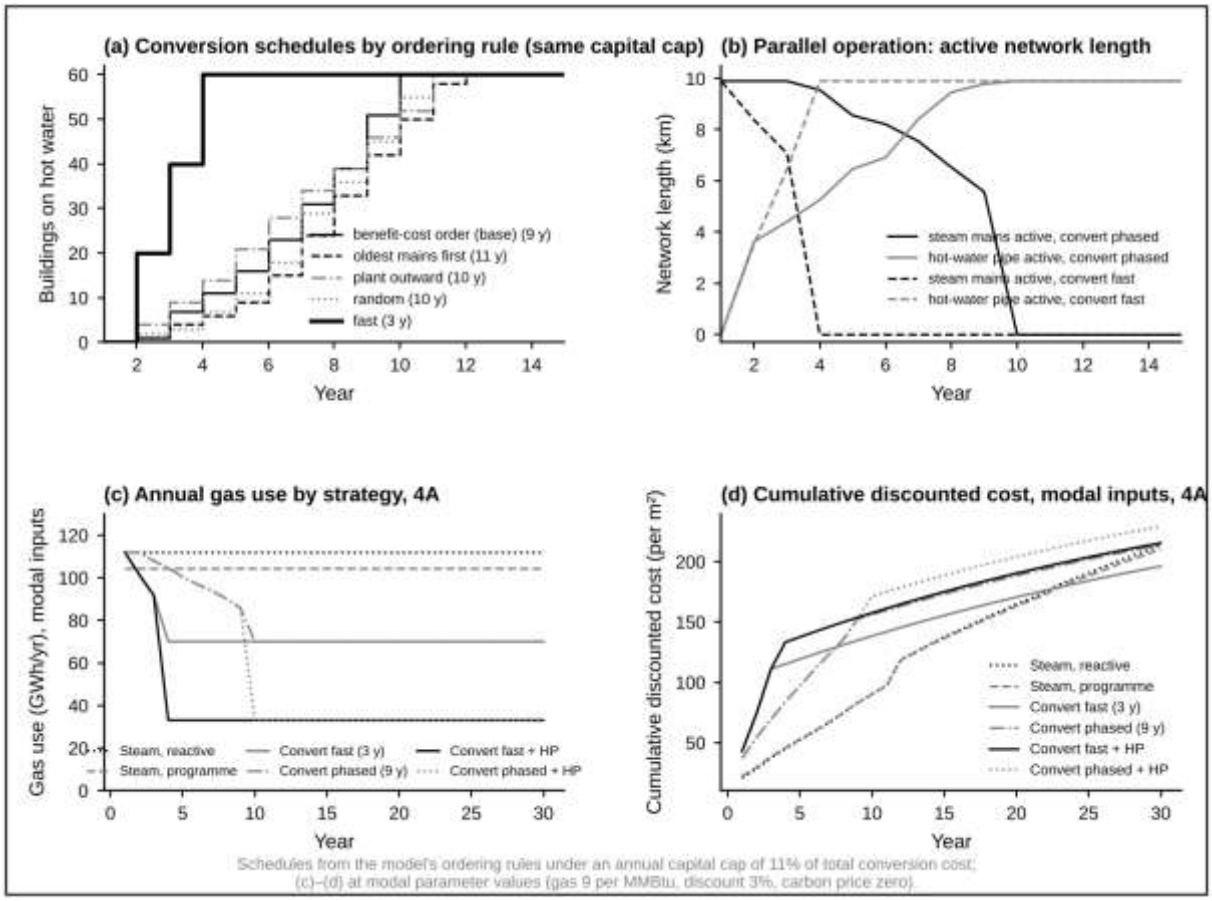
Table 8: Fuel, heat delivered, loss shares, distribution loss, delivered efficiency and water use by climate for steam (reactive and programme, year 1) and hot water (year 30)

Case	Fuel (GWh/yr)	Heat delivered to buildings (GWh/yr)	Share of fuel (%): stack and standby / pipe / traps / condensate, flash, blowdown / converter	Distribution loss (% of plant output)	Delivered efficiency (%)	Makeup and blowdown water (1,000 m³/yr)
3A warm-humid — Steam, reactive (year 1)	80.6	39.5	23.5 / 13.4 / 6.0 / 7.4 / 0.7	35	49	34
3A warm-humid — Steam, programme (year 1)	73.0	39.5	23.2 / 13.2 / 1.3 / 7.5 / 0.8	29	54	31
3A warm-humid — Hot water (year 30)	45.7	37.3	10.0 / 1.8 / – / – / 6.3 (local process)	2.2	87	≈ 0
4A mixed-humid — Steam, reactive (year 1)	112.0	61.0	22.3 / 10.6 / 4.3 / 7.5 / 0.8	29	54	48
4A mixed-humid — Steam, programme (year 1)	104.2	61.0	22.0 / 10.1 / 0.9 / 7.6 / 0.9	24	59	45
4A mixed-humid — Hot water (year 30)	70.2	58.8	10.2 / 1.4 / – / – / 4.1 (local process)	1.7	87	≈ 0
5A cool-humid — Steam, reactive (year 1)	140.5	80.4	21.8 / 9.1 / 3.4 / 7.6 / 0.9	26	57	61
5A cool-humid — Steam, programme (year 1)	132.7	80.4	21.6 / 8.6 / 0.7 / 7.6 / 0.9	22	61	57
5A cool-humid — Hot water (year 30)	92.1	78.2	10.3 / 1.2 / – / – / 3.1 (local process)	1.4	88	≈ 0
6A cold — Steam, reactive (year 1)	168.7	99.8	21.7 / 7.8 / 2.9 / 7.6 / 0.9	23	59	73
6A cold — Steam, programme (year 1)	160.8	99.8	21.5 / 7.3 / 0.6 / 7.6 / 0.9	20	62	70
6A cold — Hot water (year 30)	114.1	97.6	10.4 / 1.1 / – / – / 2.5 (local process)	1.3	88	≈ 0

Schedules, parallel operation and trajectories

Figure 6 shows the schedules and the trajectories they produce at modal inputs. Under the capital cap, the benefit-cost order converts 60 buildings in nine years and the alternative orders in ten to eleven; the fast programme converts them in three. Parallel operation is the consequence (Figure 6b): under the phased programme the hot-water trunk is installed in the first two years and 3.7 km of hot-water pipe is live by the end of year 2 while 9.9 km of steam main is still live, and both networks exceed 5 km for about six years; under the fast programme the overlap lasts two years. Annual gas use (Figure 6c) falls from 110 GWh to 70 GWh in the fourth year under the fast programme but only by the tenth year under the phased one, and to 33 GWh when the heat-pump plant comes on. The cumulative discounted cost (Figure 6d) shows the shape of the decision: the conversion strategies spend 90–135 per m² in their first years and then run below the steam strategies' slope, and at modal inputs the fast conversion's curve crosses the steam programme's in the 4A climate only near the end of the horizon, which is why the payback statistics reported below are long.

Figure 6: Conversion schedules and trajectories: (a) buildings converted per year by ordering rule and the fast programme, (b) active steam and hot-water network length (parallel operation), (c) annual gas use by strategy, (d) cumulative discounted cost at modal inputs



Life-cycle cost and its components (RQ2)

Table 9 gives the thirty-year life-cycle cost per m² for all strategies and climates and Figure 7 and Table 10 its decomposition. Keeping steam costs 157–160 per m² in the warm climate and 276–280 in the cold one; in the mixed-humid and cold climates gas is 126–204 of this, the renewal of mains reaching the end of their life and the year-12 boiler replacement 44–47, staff 18, water 9–14, failures 2 and maintenance 5–10. Fast conversion costs 163 per m² in 3A and 260 in 6A: its capital of 95–100 per m² (undiscounted 97–107, or 54–60 million for the campus) is set against gas savings of 36–50, avoided renewal of 44–47, staff savings of 9, water savings of 8–12 and failure savings of 2, while its residual value of 4–5 per m² at the horizon is smaller than the 11 that renewed steam mains would carry. The

phased programme costs 15–18 per m² more than the fast one in every climate — not because its capital is higher (it is lower, 87–90, because the hot-water boilers and decommissioning come later and residual values are higher) but because it pays 10 per m² of steam renewal and boiler life-extension during the overlap, 5 more in staff, 9–12 more in gas and 1–2 more in water. The heat-pump variants add 13–23 per m² at the modal electricity price of 0.12 per kWh and gas price of 9 per MMBtu: electricity of 42–69 per m² replaces gas of 38–64, and the plant costs 18–22, so at these prices the heat pumps buy emissions rather than money. Gross capital for fast conversion of 97–107 per m² is close to the 110 per m² of UBC's programme (UBC, n.d.-b), and its internal-retrofit component — 0.3–0.7 of buildings at 40–100 per m² — is the single largest and least certain item.

Table 9: Thirty-year life-cycle cost per m² by climate and strategy (mean and 5th–95th percentiles) with undiscounted conversion capital

Climate	Steam, reactive	Steam, programme	Convert fast (3 y)	Convert phased (9 y)	Convert fast + heat pumps	Convert phased + heat pumps	Undiscounted conversion capital per m²: fast / fast + HP
3A warm-humid	160 (120–213)	157 (118–205)	163 (133–197)	177 (145–215)	176 (149–205)	188 (158–220)	97 / 112
4A mixed-humid	204 (149–275)	200 (149–268)	199 (160–247)	214 (172–265)	217 (183–255)	228 (190–271)	102 / 122
5A cool-humid	243 (176–331)	239 (175–323)	231 (183–291)	247 (195–311)	253 (211–300)	264 (218–316)	106 / 131
6A cold	280 (201–385)	276 (200–376)	260 (202–332)	278 (216–354)	283 (234–338)	295 (241–357)	107 / 132

Figure 7: Life-cycle cost decomposition by strategy in four climates: capital, steam renewal and boiler replacement, gas, electricity, staff, maintenance, failures, water and residual value, with net life-cycle cost

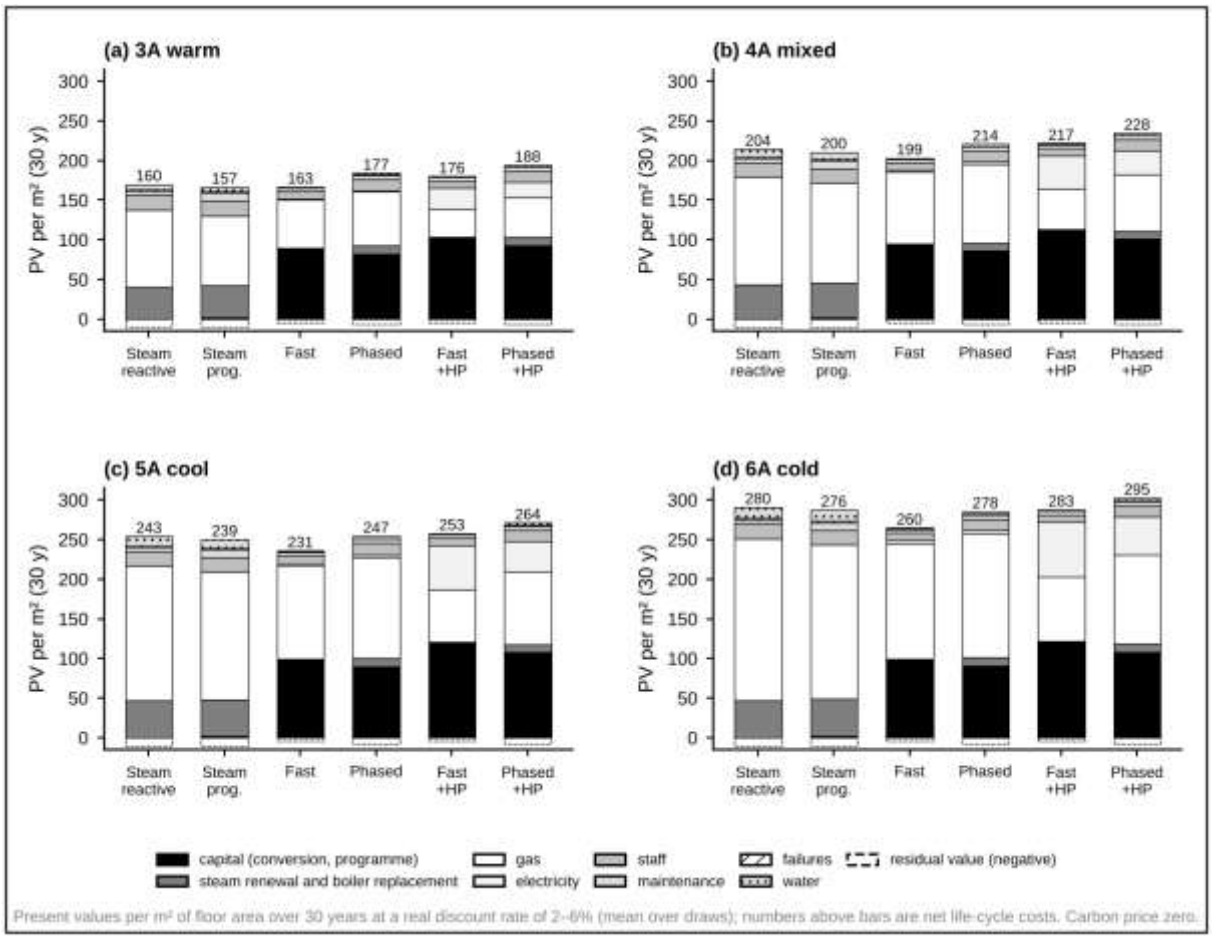


Table 10: Present value of life-cycle cost components per m² by strategy in the mixed-humid and cold climates

Present value per m²	Steam, reactive	Steam, programme	Convert fast (3 y)	Convert phased (9 y)	Convert fast + heat pumps	Convert phased + heat pumps
4A mixed-humid: Capital	0.0	1.7	94.9	86.5	112.8	101.0
4A mixed-humid: Steam renewal and boiler replacement	44.0	44.0	0.0	9.8	0.0	9.8
4A mixed-humid: Gas	135.6	126.2	90.3	99.4	51.8	72.0
4A mixed-humid: Electricity	0.0	0.0	2.8	2.4	41.7	29.2
4A mixed-humid: Staff	18.4	18.4	9.3	14.1	9.3	14.1
4A mixed-humid: Maintenance	4.9	9.6	4.8	5.4	4.8	5.4
4A mixed-humid: Failures	2.2	2.2	0.2	0.6	0.2	0.6
4A mixed-humid: Water	9.4	8.7	1.0	2.4	1.0	2.4
4A mixed-humid: Residual value	−10.6	−10.6	−4.4	−6.9	−4.4	−6.9
4A mixed-humid: Net life-cycle cost	203.8	200.2	198.9	213.7	217.2	227.6
6A cold: Capital	0.0	1.7	99.5	90.3	121.8	108.4
6A cold: Steam renewal and boiler replacement	47.2	47.2	0.0	10.7	0.0	10.7
6A cold: Gas	204.2	194.6	144.9	156.8	81.3	111.4
6A cold: Electricity	0.0	0.0	4.7	3.9	69.0	48.3
6A cold: Staff	18.4	18.4	9.3	14.1	9.3	14.1
6A cold: Maintenance	4.9	9.6	4.8	5.4	4.8	5.4
6A cold: Failures	2.2	2.2	0.2	0.6	0.2	0.6
6A cold: Water	14.2	13.6	1.4	3.7	1.4	3.7
6A cold: Residual value	−11.0	−11.0	−4.6	−7.4	−4.6	−7.4
6A cold: Net life-cycle cost	280.0	276.3	260.2	278.1	283.1	295.1

Probabilities, break-even values and the value of information (RQ3)

Figure 8 and Table 11 report the Monte Carlo outcomes. The life-cycle cost distributions overlap heavily (Figure 8a): in the cold climate the 5th–95th percentile ranges span 200–376 per m² for the steam programme and 202–332 for fast conversion. The probability that the conversion family is least-cost rises with heating degree-days — 33% in 3A, 51% in 4A, 65% in 5A and 78% in 6A — and within the family the fast programme takes almost all of it (29, 45, 56 and 65%), the heat-pump variant 4–12% and the phased programmes none, because the fast programme dominates them draw by draw. Within the steam family the programme is least-cost in 17–55% of draws and reactive maintenance in 6–12%. The median saving of fast conversion against the steam programme runs from −7 per m² in the warm climate (5th–95th: −31 to +20) to +15 in the cold one (−16 to +53), and the pairwise probability that fast conversion is cheaper equals the family probability. The expected value of perfect information is 4.0, 6.8, 4.9 and 3.9 per m² — 2.2–3.8 million for the campus — and peaks in the mixed-humid climate where the decision is closest, which is where a trap survey, a condition assessment of the mains and a building-by-building retrofit scoping study are worth commissioning before deciding. Phased conversion's cumulative discounted cost falls below the steam programme's within the horizon in only 10% of draws in 3A and 50% in 6A, and almost never within 20 years; the decision is a thirty-year one, and the institutional figures of 35-year savings horizons are consistent with that (Stanford University, 2015).

Break-even values locate the decision on the price axes. The median gas price at which fast conversion equals the steam programme is 12.1 per MMBtu in 3A (5th–95th: 5–23), 9.6 in 4A, 8.1 in 5A and 6.8 in 6A, against a sampled range of 6–15 with mode 9; for the phased programme it is 20.7, 15.3, 12.5 and 10.6. The median break-even hot-water pipe cost for fast conversion is 1,366 per metre in 3A and 2,782 in 6A against a sampled range of 1,200–2,600, so in the cold climate conversion pays at the top of the pipe-cost range and in the warm one only at the bottom. Figure 9 draws these distributions and the phasing results: the cost of a slower programme rises almost linearly with duration — 10–11 per m² for

six years, 16–18 for ten and 22–26 for fifteen relative to three — while the parallel-operation staff cost rises from 9 to 18 per m² and the peak annual capital outlay falls from 51–55 to 25–30 per m²; the ordering rule matters less, with the plant-outward order 0.8–1.9 per m² cheaper than the benefit-cost order at the same cap because it shortens the overlap, oldest-first 0.9–2.3 dearer because it stretches it, and a random order 3.8–5.6 dearer. The duration result is the model's clearest message about implementation: phasing buys lower annual capital at a price of about 1.0–1.2 per m² per year of programme, because the fixed costs of the steam plant and the losses of two networks run until the last building converts.

Figure 8: Monte Carlo outcomes: (a) life-cycle cost distributions in the cold climate, (b) savings of each conversion strategy against the steam programme with 5th–95th percentiles, (c) probability of least cost by climate, (d) probability that conversion is least-cost under scenarios

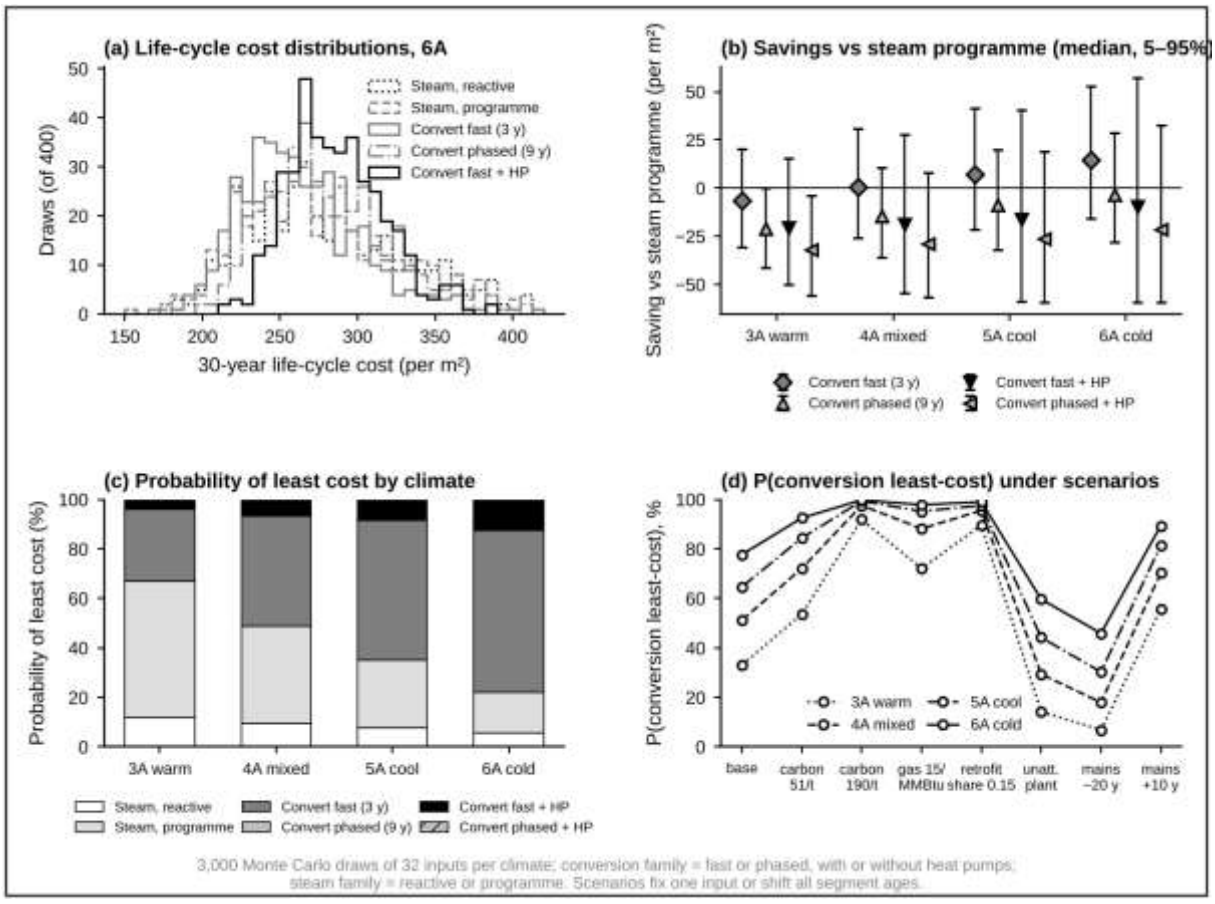


Table 11: Probability of least cost, conversion-family and pairwise probabilities, savings distribution, EVPI, break-even gas price and pipe cost, payback and best strategy by climate

Climate	P(least cost), %: reactive / programme / fast / phased / fast+HP / phased+HP	P(conversion family)	P(cheaper than programme): fast / phased / fast+HP	Fast minus programme LCC per m², median (5th–95th)	EVPI per m²	Break-even gas price (per MMBtu): fast, median (5th–95th) / phased	Break-even pipe cost, fast (per m)	Phased payback within 30 y (%)	Best by expected LCC
3A warm-humid	12 / 55 / 29 / 0 / 4 / 0	33	33 / 5 / 15	−7 (−31 to 20)	4.0	12.1 (5–23) / 20.7	1,366 (−340 to 3238)	10	Steam, programme
4A mixed-humid	9 / 39 / 45 / 0 / 7 / 0	51	51 / 16 / 22	1 (−26 to 31)	6.8	9.6 (4–18) / 15.3	1,868 (89–3949)	24	Convert fast (3 y)
5A cool-humid	8 / 28 / 56 / 0 / 8 / 0	65	65 / 28 / 29	7 (−21 to 41)	4.9	8.1 (3–16) / 12.5	2,280 (429–4556)	38	Convert fast (3 y)
6A cold	6 / 17 / 65 / 0 / 12 / 0	78	78 / 42 / 39	15 (−16 to 53)	3.9	6.8 (2–13) / 10.6	2,782 (802–5307)	50	Convert fast (3 y)

Figure 9: Break-even and phasing: (a) break-even gas price, (b) break-even pipe cost, (c) cost of a slower programme, (d) parallel-operation staff cost and peak capital by programme duration

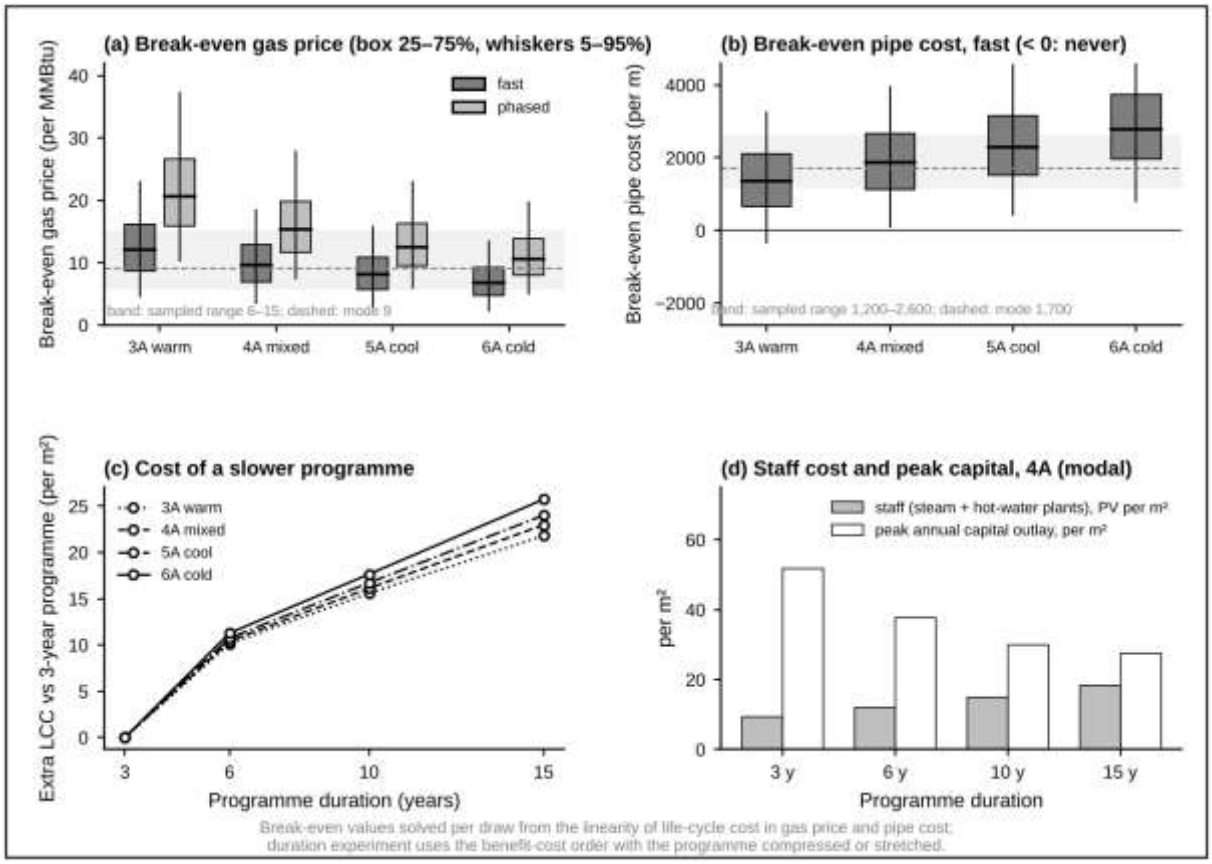


Table 12 gives the scenarios (Figure 8d). A carbon price of 51 per tonne raises the conversion probability to 54–93% across the climates and 190 per tonne to 92–100%, at which point the heat-pump variant becomes the most probable least-cost strategy (52–72%) because it removes two-thirds of the remaining gas. Gas fixed at 15 per MMBtu gives 72–98%. An internal-retrofit share of 0.15 — a campus whose buildings already have hot-water coils fed by converters — gives 90–99%, and with a carbon price of 51 as well, 97–100%. The scenarios that lower the probability are as informative: an unattended steam plant with the same staffing as hot water lowers it to 14–60%, a 25% higher pipe cost to 23–66%, and steam mains 20 years younger to 7–46%, while mains 10 years older raise it to 56–89%. The conversion decision is, in the model's own numbers, an asset-renewal decision as much as an energy decision: where the mains are near the end of their life and would have to be renewed anyway, conversion is the cheaper way to renew them; where they are young, the energy saving alone does not carry the capital at a gas price of 9.

Table 12: Scenarios (carbon price, gas price, retrofit scope, staffing, pipe cost, asset age) and phasing experiments (ordering rule, programme duration, staff cost, peak capital) by climate

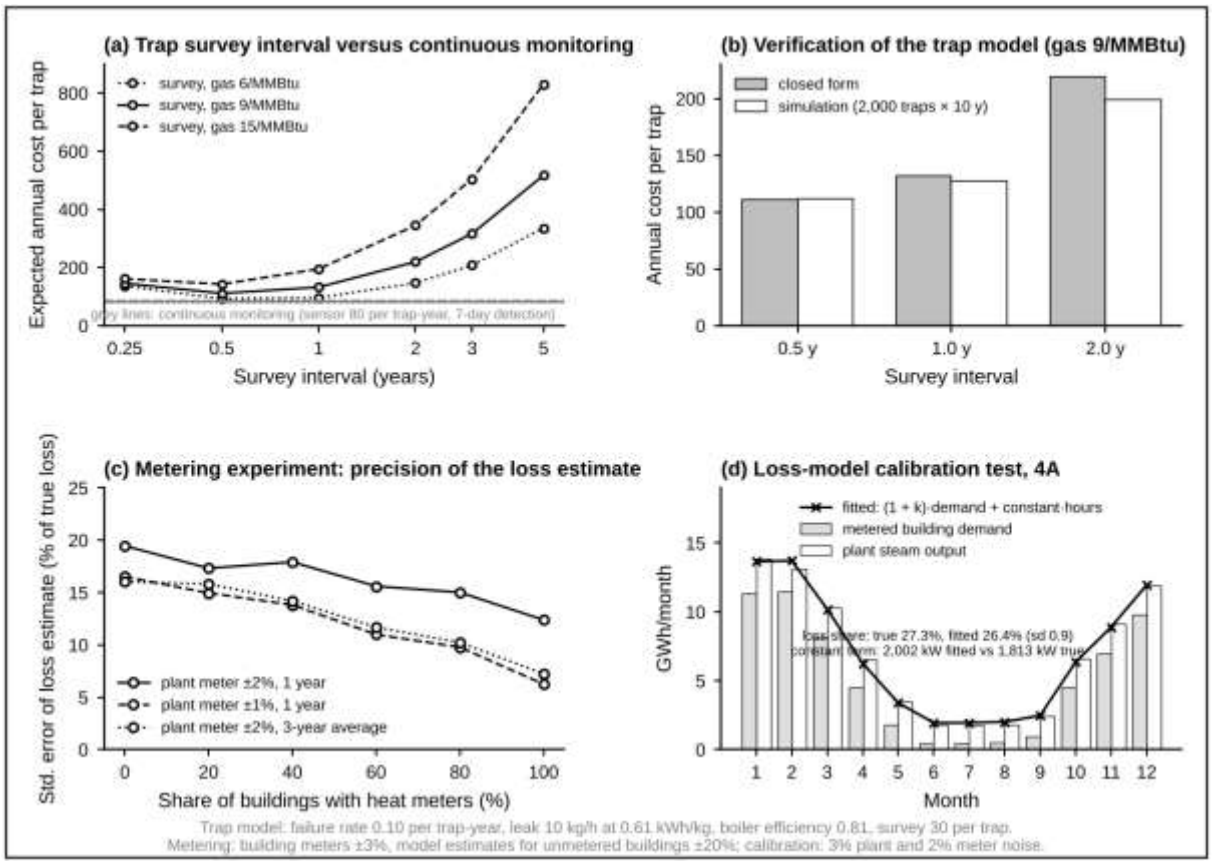
Experiment	3A warm-humid	4A mixed-humid	5A cool-humid	6A cold
Base case: P(conversion family least-cost), %	33	51	65	78
Scenario — Carbon price 51 per tonne: P(conversion), %	54	72	84	93
Scenario — Carbon price 190 per tonne: P(conversion), %	92	98	99	100
Scenario — Gas 15 per MMBtu (fixed): P(conversion), %	72	88	95	98
Scenario — Internal retrofit share 0.15: P(conversion), %	90	96	98	99
Scenario — Retrofit share 0.15 and carbon 51: P(conversion), %	97	99	100	100
Scenario — Unattended steam plant (same staff as hot water): P(conversion), %	14	29	44	60
Scenario — Pipe cost −25%: P(conversion), %	48	65	77	87
Scenario — Pipe cost +25%: P(conversion), %	23	38	52	66
Scenario — All mains 20 years younger: P(conversion), %	7	18	30	46
Scenario — All mains 10 years older: P(conversion), %	56	70	81	89
Phasing order — oldest mains first vs benefit-cost: ΔLCC per m² (years to complete)	+0.9 (11)	+1.9 (11)	+2.3 (11)	+2.0 (11)
Phasing order — plant outward vs benefit-cost: ΔLCC per m² (years to complete)	−1.9 (10)	−0.8 (10)	−0.8 (10)	−1.3 (10)
Phasing order — random order vs benefit-cost: ΔLCC per m² (years to complete)	+3.8 (10)	+5.3 (10)	+5.6 (10)	+5.5 (10)
Programme duration 6 y vs 3 y: ΔLCC per m² (P cheaper than programme, %)	+10.1 (11)	+10.4 (25)	+10.8 (40)	+11.3 (55)
Programme duration 10 y vs 3 y: ΔLCC per m² (P cheaper than programme, %)	+15.6 (4)	+16.1 (14)	+16.7 (26)	+17.6 (41)
Programme duration 15 y vs 3 y: ΔLCC per m² (P cheaper than programme, %)	+21.8 (0)	+23.0 (4)	+24.0 (12)	+25.7 (24)
Staff PV per m² during the programme, modal inputs: 3 / 6 / 10 / 15 y	9 / 12 / 15 / 18	9 / 12 / 15 / 18	9 / 12 / 15 / 18	9 / 12 / 15 / 18
Peak annual capital outlay per m², modal: 3 / 6 / 10 / 15 y	51 / 36 / 28 / 25	52 / 38 / 30 / 28	54 / 39 / 32 / 30	55 / 42 / 32 / 30

The data lane: trap economics, metering and calibration (RQ4)

Figure 10 and Table 13 report the three experiments. The expected cost of a failed-open trap is 1,300 per trap-year at gas 6 per MMBtu, 2,000 at 9 and 3,300 at 15, so the optimal survey interval is 0.67, 0.54 and 0.43 years at a total cost of 89, 111 and 141 per trap-year, and an annual survey costs 96, 132 and 195; the five-year interval that an unmaintained system amounts to costs 336–831 per trap-year, which for the campus's roughly 430 traps is the trap-leakage line of Table 8. Continuous monitoring at 80 per trap-year with a seven-day detection lag costs 83–86 per trap-year in total, below the optimal survey policy at every gas price, by a margin that widens with the gas price; the closed form agrees with the simulation of 2,000 traps within 1–10%. The metering experiment shows that the precision of the distribution-loss estimate is limited first by the plant meter: with a ±2% plant meter and one year of data, the standard error is 19% of the true loss with no building meters and 12% with all buildings metered, whereas a ±1% plant meter or three years of data brings the fully metered case to 6–7%. The calibration test recovers the total distribution loss from twelve months of plant and meter data to within one percentage point (true 22.2–33.1% of plant output, fitted 21.6–32.1%, standard deviation over noise 0.8–0.9), but it over-estimates the constant pipe-and-trap term by 7–15% and under-estimates the

proportional condensate term (7.1–7.7% fitted against 11%), because the two are only weakly separable in monthly data; the total loss, which is what the economics need, is identified, and the split, which the remedy needs, requires a trap survey and an insulation survey rather than more meter data.

Figure 10: Data-lane experiments: (a) steam-trap survey interval versus continuous monitoring at three gas prices, (b) verification of the trap model, (c) metering experiment, (d) loss-model calibration test on synthetic monthly data



What drives the outcome: sensitivity and the metamodel (RQ3)

Figure 11 and Table 14 give the Sobol indices and the metamodel. The inputs that matter are financial and building-side, not thermodynamic. In the mixed-humid climate the discount rate (total-order index 0.22), the internal-retrofit cost (0.18), the gas price (0.17), the retrofit share (0.15), the pipe cost (0.10) and gas escalation (0.09) explain the variance of the steam-programme-minus-conversion cost difference; in the warm climate the retrofit cost and share lead (0.22 and 0.19) and in the cold one the discount rate (0.29) and gas price (0.23). Condensate return (0.02–0.05), renewal cost (0.03–0.05), boiler efficiency, trap failure share, loss coefficients, staffing and the failure parameters each contribute less than 0.05, and the first-order indices sum to 0.99–1.00, so the model is additive in its inputs. For the heat-pump variant the gas price (0.39) and its escalation (0.21) dominate, with the electricity price (0.09) next. The metamodel reproduces the decision well: the gradient-boosting classifier identifies whether conversion is least-cost with an AUC of 0.970 and an accuracy of 89% against a base rate of 57%, the multiclass model identifies the least-cost strategy with 87% accuracy, and the regressor explains 98% of the variance of the conversion margin; gain importance is spread across the discount rate (13%), degree-days (12%), retrofit share (12%), gas price (12%), retrofit cost (8%), gas escalation (8%), renewal age (6%) and renewal cost (6%).

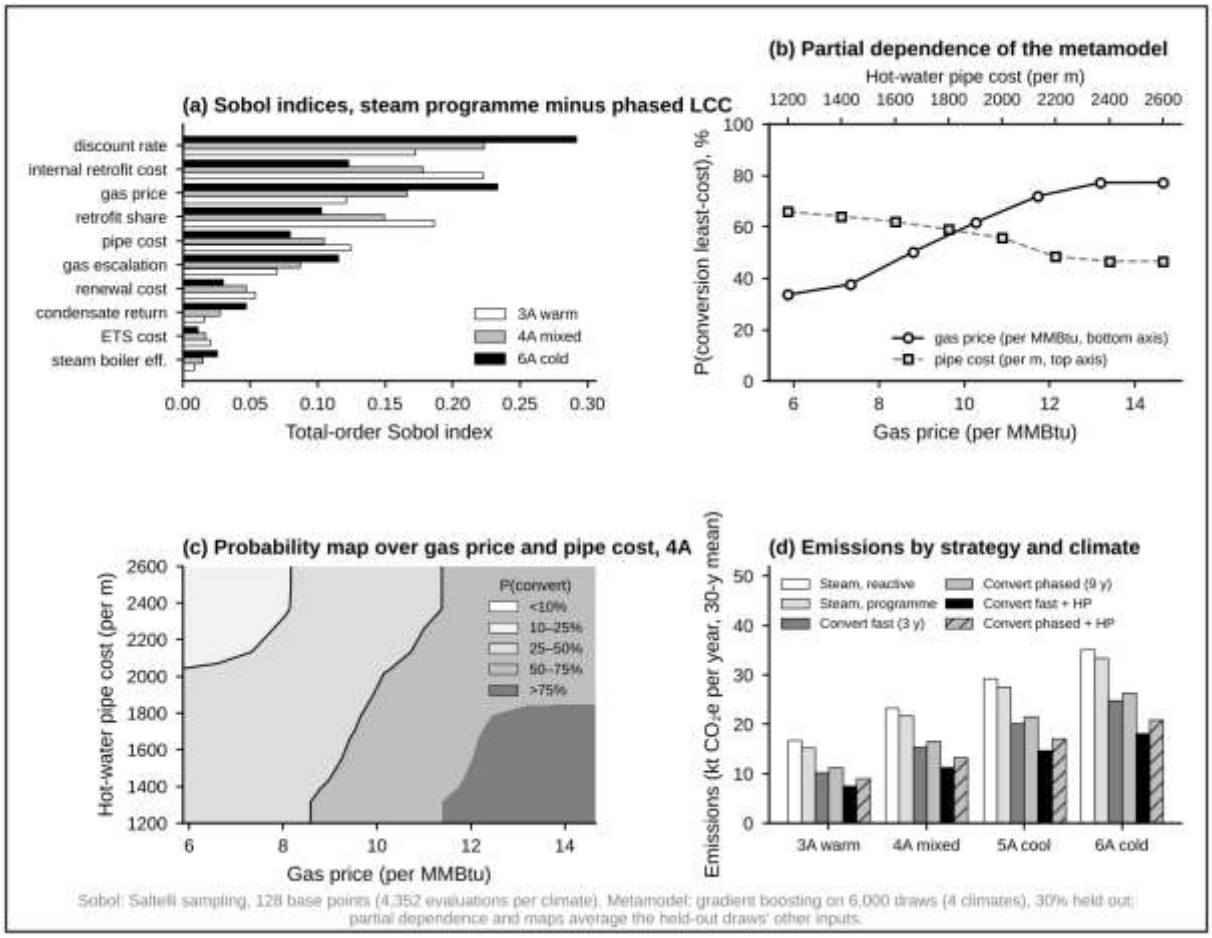
Table 13: Trap survey and monitoring economics, metering experiment and loss-model calibration results

Experiment	Setting / result	Result	Note
Trap survey economics at gas 6 per MMBtu	cost of a failed trap-year 1,319; optimal interval 0.67 y at 89 per trap-year	annual cost per trap: 0.5 y 93, 1 y 96, 2 y 147, 5 y 336	continuous monitoring 83 per trap-year (sensor 80, residual leakage 3)
Trap survey economics at gas 9 per MMBtu	cost of a failed trap-year 2,045; optimal interval 0.54 y at 111 per trap-year	annual cost per trap: 0.5 y 111, 1 y 132, 2 y 220, 5 y 517	continuous monitoring 84 per trap-year (sensor 80, residual leakage 4)
Trap survey economics at gas 15 per MMBtu	cost of a failed trap-year 3,299; optimal interval 0.43 y at 141 per trap-year	annual cost per trap: 0.5 y 142, 1 y 195, 2 y 345, 5 y 831	continuous monitoring 86 per trap-year (sensor 80, residual leakage 6)
Trap model verification (gas 9 per MMBtu)	closed form vs simulation of 2,000 traps over 10 years	0.5 y: 111 vs 112; 1 y: 132 vs 127; 2 y: 220 vs 199	agreement within the approximation of the mean failed share
Metering experiment, 4A — plant meter ±2%, 1 year	standard error of the loss estimate as % of the true loss (20% of demand)	metered share 0 / 40 / 80 / 100%: 19 / 18 / 15 / 12	model estimates for unmetered buildings ±20%; building meters ±3%
Metering experiment, 4A — plant meter ±1%, 1 year	standard error of the loss estimate as % of the true loss (20% of demand)	metered share 0 / 40 / 80 / 100%: 17 / 14 / 10 / 6	model estimates for unmetered buildings ±20%; building meters ±3%
Metering experiment, 4A — plant meter ±2%, 3-year average	standard error of the loss estimate as % of the true loss (20% of demand)	metered share 0 / 40 / 80 / 100%: 16 / 14 / 10 / 7	model estimates for unmetered buildings ±20%; building meters ±3%
Loss-model calibration, 3A warm-humid	loss share of plant output: true 33.1%, fitted 32.1% (sd over noise 0.8)	constant term: fitted 1,815 kW vs true 1,700 kW (+7%); proportional term fitted 7.1% vs true 11%	12 monthly observations, 3% plant and 2% meter noise; total loss identified, split between constant and proportional terms confounded
Loss-model calibration, 4A mixed-humid	loss share of plant output: true 27.3%, fitted 26.4% (sd over noise 0.9)	constant term: fitted 2,002 kW vs true 1,813 kW (+10%); proportional term fitted 7.1% vs true 11%	12 monthly observations, 3% plant and 2% meter noise; total loss identified, split between constant and proportional terms confounded
Loss-model calibration, 5A cool-humid	loss share of plant output: true 24.4%, fitted 23.7% (sd over noise 0.9)	constant term: fitted 2,167 kW vs true 1,915 kW (+13%); proportional term fitted 7.3% vs true 11%	12 monthly observations, 3% plant and 2% meter noise; total loss identified, split between constant and proportional terms confounded
Loss-model calibration, 6A cold	loss share of plant output: true 22.2%, fitted 21.6% (sd over noise 0.9)	constant term: fitted 2,248 kW vs true 1,958 kW (+15%); proportional term fitted 7.7% vs true 11%	12 monthly observations, 3% plant and 2% meter noise; total loss identified, split between constant and proportional terms confounded

Partial dependence shows the probability rising from 33% at 1,500 to 77% at 4,300 degree-days, matching the Monte Carlo probabilities by climate, from 34% to 77% as gas rises from 6 to 15 per MMBtu, falling from 66% to 47% as pipe cost rises from 1,200 to 2,600 per metre, and rising from 48% to 70% as renewal cost rises from 2,000 to 4,500 per metre; the map over gas price and pipe cost in 4A (Figure 11c) runs from 18% at dear pipe and cheap gas to 84% at cheap pipe and dear gas. The shallow trees are weak: a depth-3 tree reaches 71% accuracy (depth 4 also 71%) with a rule that reads "below

2,950 degree-days, convert if the retrofit share is small and the discount rate below 3.7%, or if the retrofit share is large and gas exceeds about 11 per MMBtu; above 2,950, convert unless the discount rate exceeds 4% and the retrofit share is large". The gap between the tree and the boosted model says that the decision depends on interactions among asset age, retrofit scope, prices and discount rate that a three-level rule cannot carry, and that a campus should run the probabilistic analysis with its own inputs rather than apply a rule.

Figure 11: Sensitivity, metamodel and emissions: (a) Sobol total-order indices in three climates, (b) partial dependence on gas price and pipe cost, (c) probability map over gas price and pipe cost, (d) emissions by strategy and climate



Emissions and abatement cost (RQ4)

Figure 11d and Table 14 close with emissions. Year-1 emissions of the reactive steam system are 16.8 kt CO_2 e in 3A and 35.1 kt in 6A; over thirty years with a declining grid, the steam programme emits 456–1,004 kt, fast conversion 306–748 kt (26–33% less), phased conversion 21–26% less, and the heat-pump variants 46–50% less, with the smaller reductions in the colder climates where the share of fuel in distribution losses is smaller. The mean abatement cost of fast conversion against the steam programme is 23 per tonne in the warm climate and negative — it is cheaper and cleaner — in the three colder ones; the heat-pump variant abates at 8–48 per tonne and the phased programme at 5–100. Against the EPA's central social cost of carbon of 190 per tonne, every conversion strategy is worth its cost in every climate in this model, and against 51 per tonne all but the phased programme in the warm and mixed climates (EPA, 2023; Rennert et al., 2022); the carbon-price scenarios of Table 12 say the same from the decision side.

Table 14: Sobol first- and total-order indices by input in three climates and against the heat-pump variant, metamodel discrimination, importance, partial dependence and the depth-3 screening rule

Input / metamodel item	3A: S1 / ST	4A: S1 / ST	6A: S1 / ST	4A vs heat-pump variant: ST
disc	0.13 / 0.17	0.17 / 0.22	0.22 / 0.29	0.13
int_cost	0.22 / 0.22	0.18 / 0.18	0.13 / 0.12	0.10
p_gas	0.13 / 0.12	0.16 / 0.17	0.21 / 0.23	0.39
int_share	0.18 / 0.19	0.15 / 0.15	0.11 / 0.10	0.09
pipe_cost	0.10 / 0.12	0.08 / 0.10	0.06 / 0.08	0.06
esc_gas	0.01 / 0.07	0.02 / 0.09	0.04 / 0.11	0.21
renewal_cost	0.05 / 0.05	0.05 / 0.05	0.03 / 0.03	0.03
r_cond	0.00 / 0.02	0.01 / 0.03	0.03 / 0.05	0.02
ets_cost	0.02 / 0.02	0.01 / 0.02	0.00 / 0.01	0.01
eta_steam	0.01 / 0.01	0.01 / 0.01	0.02 / 0.03	0.01
Sum of first-order indices	0.99	1.00	1.00	0.96
Metamodel: discrimination	AUC 0.970; accuracy 89.1% (base rate 57%)	multiclass accuracy 87.1%	R^2 of conversion margin 0.979	4,200 train / 1,800 test
Metamodel: gain importance (top 8)	disc 13%; hdd 12%; int_share 12%; p_gas 12%	int_cost 8%; esc_gas 8%; renew_age 6%; renewal_cost 6%	—	—
Partial dependence: P(conversion), %	HDD 1500→4300: 33→77	gas 6→15 per MMBtu: 34→77; pipe 1,200→2,600 per m: 66→47	steam staff 4.5→6.5 FTE: 55→60	renewal cost 2,000→4,500 per m: 48→70
Depth-3 tree (accuracy 71%)	HDD ≤ 2,950: convert if retrofit share ≤ 0.47 and discount rate ≤ 3.7%, or if retrofit share > 0.47 and gas > 0.037 per kWh (≈ 11 per MMBtu)	HDD > 2,950: convert if discount rate ≤ 4.0%, or if discount rate > 4.0% and retrofit share ≤ 0.51	depth-4 accuracy 71%	rule re-estimated from the final results file; thresholds model-specific

Discussion

What the model says about the steam-to-hot-water decision

Four results summarise the analysis. First, the efficiency case is large and robust: a campus steam system under reactive maintenance delivers about half of its fuel as heat in buildings, hot water delivers nearly nine-tenths, and conversion cuts gas use by a third and thirty-year emissions by a quarter to a third, by a half with heat pumps. These magnitudes do not depend on the economic assumptions and they match the institutional reports of 20–25% energy savings and 55% versus 75–90% efficiency (UBC, 2011a; Wesleyan University, 2024b; Cornell University, 2025). Second, the economic case is conditional and the conditions are identifiable: at a gas price of 9 per MMBtu and no carbon price, fast conversion is least-cost with probability 33% in the warm climate and 78% in the cold one, and the probability moves by 15–55 points with the age of the mains, the scope of the internal retrofit, the staffing rules of the steam plant, the carbon price and the gas price. The largest of these — asset age — says that conversion is an asset-renewal decision: where the mains would have to be renewed anyway, converting them is the cheaper renewal; where they are young, the energy saving does not carry the capital. Third, the maintenance programme is the cheapest action and should precede any conversion decision: it pays in 86–89% of draws, halves the distribution loss that conversion would otherwise be credited with, and is the measurement platform (trap survey, insulation survey, plant-minus-meter balance) that the decision needs. Fourth, phasing is expensive: 15–18 per m^2 for nine years against three, about 1 per m^2 per year of programme, because the steam plant's fixed costs and the losses of two networks persist until the last building converts; a campus that phases for capital reasons should know

the price and should order the work to shorten the overlap rather than to pick the oldest or most lossy branches first.

These results are consistent with the documented conversions and add what they lack. Stanford, UBC, Cornell, Wesleyan and the others report point projections of energy, emissions and savings (Stanford University, 2015; UBC, 2011b; Cornell University, 2016; Wesleyan University, 2024a); the model shows that the same inputs, with their uncertainties, produce probabilities of 33–78% rather than certainties, and it says which inputs the uncertainty comes from. The district heating literature's emphasis on heat density, return temperature and low-temperature operation (Persson & Werner, 2011; Gadd & Werner, 2014; Lund et al., 2018) appears in the model as the density gradient of distribution losses and the condensing-boiler dependence on return temperature; the steam-system literature's trap and insulation measures (U.S. DOE, 2012b; U.S. DOE, 2012c; U.S. DOE FEMP, n.d.) appear as the programme that halves the loss; and the maintenance-optimisation literature's inspection model (Barlow & Hunter, 1960; Dekker, 1996) appears as the survey-interval result that continuous monitoring now dominates at the sensor costs assumed. The heat-pump result deserves comment: at the modal prices the heat-pump plant buys emissions, not money, and it becomes the most probable least-cost strategy only with a carbon price near the EPA's central value or with electricity cheap relative to gas, which is the spark-spread condition of the heat-pump literature (Deetjen et al., 2021; Wilson et al., 2024; IEA, 2022) transposed to a district system. The value of low-temperature hot water is that it makes the heat-pump option available when those conditions arrive (Lund et al., 2021; Østergaard & Andersen, 2016); the model treats it as a strategy, and an application would treat it as an option (Dixit & Pindyck, 1994; de Neufville & Scholtes, 2011).

Implications for the framework and for practice

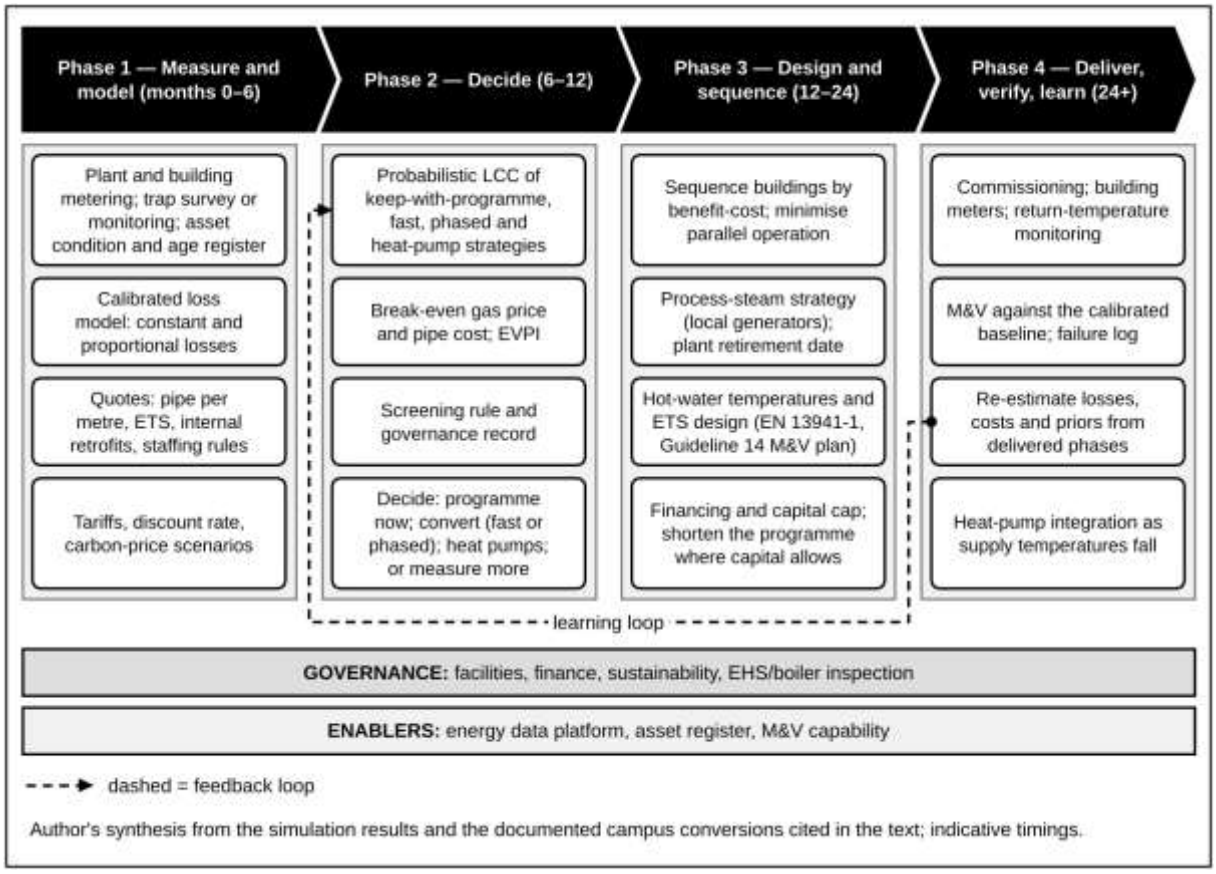
The framework's value lies in turning these conditional results into a procedure. The Sobol analysis says what to measure: the retrofit scope of the buildings (a survey of coils, radiators and converters), the age and condition of the mains (the asset register and a condition assessment), the staffing rules (the inspection authority's requirements), and the campus's own loss balance (plant and building meters, a trap survey). The value of information says when: at 4–7 per m², or 2–4 million for this campus, those studies are worth commissioning in every climate and most in the mixed one, where the decision is closest; they cost a small fraction of that. The data-lane experiments say how: a plant-minus-meter balance identifies the total distribution loss to within a percentage point if the plant meter is good and the data span more than a year, a trap survey separates the components, and continuous trap monitoring is cheaper than any survey interval at any gas price. The phasing analysis says in what order and how fast: shorten the overlap, retire the steam plant at a known date, and price each year of delay at about 1 per m². And the probabilities say how to present the decision to a governing body: not as a payback period but as "fast conversion is least-cost in 51% of plausible futures, with a median saving of 1 per m² and a 5th–95th range of −26 to +31, rising to 72% with a carbon price of 51 and to 96% if the retrofit scope is small", which is the form in which a decision under uncertainty should be taken (Morgan & Henrion, 1990; Keeney & Raiffa, 1993; Spiegelhalter, 2017).

Four practical implications follow. Programme first: a trap-and-insulation programme is cheap, pays with high probability and produces the data that the conversion decision needs; a campus that converts without one credits conversion with losses it could have removed for far less. Assets before energy: the conversion case should be built on the renewal plan for the mains, because avoided renewal is as large a benefit as gas in the model and is the benefit that institutional reports rarely state. Scope the buildings: the internal retrofit is the largest and least certain cost, and a building-by-building survey changes the probability more than any thermodynamic refinement. Shorten the programme: where capital allows, a three-year conversion is worth 15–18 per m² more than a nine-year one; where it does not, order the work plant-outward and fix the plant's retirement date.

Figure 12 arranges these into a roadmap. Phase 1 measures and models: plant and building metering, a trap survey or monitoring, an asset condition and age register, the calibrated loss model, quotes for pipe, transfer stations and internal retrofits, staffing rules, tariffs, discount rate and carbon scenarios. Phase 2 decides: the probabilistic life-cycle cost of the programme, fast, phased and heat-pump strategies, break-even values and the value of information, the screening rule and a governance record, and a decision to run the programme now, convert fast or phased, add heat pumps, or measure more.

Phase 3 designs and sequences: buildings ordered to minimise parallel operation, a process-steam strategy and a plant retirement date, hot-water temperatures and transfer-station design under EN 13941-1 with a Guideline 14 measurement-and-verification plan (CEN, 2019; ASHRAE, 2014), and the capital plan. Phase 4 delivers, verifies and learns: commissioning and building meters, return-temperature monitoring, M&V against the calibrated baseline, a failure log, re-estimation of losses, costs and priors from delivered phases, and heat-pump integration as supply temperatures fall (Katipamula & Brambley, 2005; Kim & Katipamula, 2018; Mills, 2011).

Figure 12: Implementation roadmap for a data-driven steam-to-hot-water conversion decision in four phases, with governance and enabler bands and a learning loop



Analytics practice: data, judgement and governance

The framework is an analytics artefact as well as an engineering one, and three features of analytics practice bear on its use. The first is data quality and provenance. The inputs with the largest Sobol indices — retrofit scope, asset age, prices, discount rate — are the ones most often entered as assumptions, and the claims that circulate about steam losses and conversion savings are, as Table 1 shows, a mixture of projections, achieved results, misattributions and figures that cannot be found; the costs of poor data quality are the costs of decisions taken on such figures (Haug et al., 2011; Hazen et al., 2014). The framework's data lane records the provenance of each input and the metamodel's importance ranking says which to verify first. The second is judgement. The framework produces probabilities and break-even values, not decisions; the decision remains with the institution, which brings constraints the model does not have — disruption, financing, the academic calendar, a carbon commitment with a date (Second Nature, n.d.) — and whose adjustments should be explicit and recorded rather than habitual (Fildes et al., 2009; Agrawal et al., 2018). Presenting the result as a probability with a range counters the anchoring on a single payback figure that the behavioural literature predicts (Tversky & Kahneman, 1974; Kahneman, 2011), and the shallow tree, weak as it is, gives a reason that can be challenged (Rudin, 2019; Lipton, 2018). The third is governance. A conversion programme that fixes a campus's heating infrastructure for fifty years is a risk-management decision

in the sense of ISO 31000 — identify, analyse, evaluate, treat and record (ISO, 2018) — and the framework's artefacts (inputs with provenance, Monte Carlo results, value of information, the decision with its reasons, the M&V plan) are that record. Studies of analytics capability find that the return on such tools comes with the complementary routines — data stewardship, decision rights, review — rather than with the tools (Mikalef et al., 2019; Brynjolfsson et al., 2021; Davenport & Ronanki, 2018); the roadmap's governance band, which includes the boiler-inspection authority, makes those routines explicit, and the human–AI interaction guidelines of making capability and uncertainty visible and supporting correction (Amershi et al., 2019; Shneiderman, 2020) describe how the outputs should be presented.

Limitations and further research

Table 15 lists the assumptions and their likely effects. The campus is synthetic, with assigned ages and insulation condition; the steam losses rest on stylised coefficients rather than a trap census; the hot-water system is at the optimistic end of institutional efficiencies; the steam plant has no cogeneration, which on a campus with CHP changes both costs and emissions (Wu & Wang, 2006; Mago & Chamra, 2009; de Chalendar et al., 2019a); the internal-retrofit scope, the staffing difference and the failure hazard are the least-known inputs and the most influential; the three-year conversion is assumed feasible without modelling disruption, procurement or financing; the heat-pump variant has a fixed share and seasonal COP without hourly dispatch, storage sizing or demand charges; emissions use average grid factors without refrigerant leakage or embodied carbon of pipe (Siler-Evans et al., 2012); and the metamodel reproduces the model, not reality — its screening rule (71% against a 57% base rate) is weak and is offered as a form, not a recommendation. Each of these can move the results, and the direction is mostly known: measured losses would change the benefit by tens of per cent in either direction; CHP would favour keeping steam where the plant is young and favour conversion to a heat-recovery plant where it is not; disruption costs would favour phasing; hourly heat-pump dispatch with storage would lower the heat-pump cost; and embodied carbon would raise the abatement cost modestly. The evaluation is artificial in the design-science sense (Venable et al., 2016); the next step in the design cycle is a naturalistic evaluation on a campus with metered plant and building data, a trap survey, an asset register, quotes and a recorded decision.

Three research directions follow. The first is the coupling of the economic framework to thermo-hydraulic network simulation and building-side models, so that the probabilistic analysis runs on the engineering tools that designers use and so that return temperatures, supply reset and heat-pump dispatch are simulated rather than sampled (van der Heijde et al., 2017; Allegrini et al., 2015; Guelpa et al., 2016). The second is the valuation of staged conversion as a real option — a hot-water trunk that can be extended, a plant retirement date that can be brought forward, a heat-pump plant that can be added when prices move — under uncertain carbon and energy prices (Dixit & Pindyck, 1994; Fernandes et al., 2011; de Neufville & Scholtes, 2011). The third is empirical: a registry of campus conversions with their inputs and outcomes — trap survey results, measured distribution losses before and after, pipe and retrofit costs per metre and per m², programme durations, and the gap between projected and achieved savings — from which the priors of this model could be estimated rather than assumed, and against which the framework's probabilities could be scored.

Table 15: Assumptions, limitations, likely effects on results and how to test with real data

Assumption or limitation	Likely effect on results	How to test with real data
Synthetic campus (60 buildings, spanning-tree network, assigned ages and insulation condition); no measured campus	Magnitudes are illustrative; the age and heat-density gradients drive the conversion case and would differ by campus	Replace with the asset register, GIS network and metered loads of the campus
Steam losses from stylised coefficients (pipe U-values, degraded share, trap leak rate, condensate return); no steam-trap population census	Distribution loss of 21–32% of plant output is within the Cornell and industry ranges but is an assumption, not a measurement	Trap survey, insulation survey, plant-minus-meter balance (Figure 10, Table 13)
Hot-water losses from pre-insulated twin-pipe coefficients; return temperatures sampled, not simulated from building controls	Hot-water delivered efficiency (≈ 88%) is at the optimistic end of institutional figures (75–90%)	Return-temperature monitoring at ETS; M&V against the calibrated baseline
Steam boiler efficiency with a stylised standby penalty; no CHP, economisers or flue-gas condensation	A campus with CHP or a modern plant has lower steam-side costs and emissions than modelled	Plant fuel and output meters; CHP electricity credit in the LCC
Internal retrofit scope (share of buildings needing terminal replacement, cost per m²) is the largest conversion cost and the least known	Sobol index 0.3–0.5 in warm climates; retrofit share 0.15 raises the conversion probability by 25–55 points	Building-by-building survey of coils, radiators and converters before deciding
Attended steam plant staffing and licensing modelled as a fixed FTE difference; jurisdiction-dependent	Removing the difference lowers the conversion probability by 18–25 points	Confirm boiler-operator rules with the inspection authority (National Board synopsis)
Failure hazard and renewal age for steam mains are stylised; outage costs are lump sums	Asset age is a first-order driver (±20 years shifts the probability by 20–30 points)	Failure log, condition assessment and renewal plan of the campus
Fast (3-year) conversion assumed feasible; disruption, procurement and financing constraints not modelled	The cost of phasing (≈ 1 per m² per year of programme) understates the practical constraints that make phasing common	Capital plan and contractor capacity; real-options valuation of staged programmes
Heat-pump variant with a fixed share and seasonal COP; no hourly dispatch, storage sizing or demand charges	Heat-pump economics at gas 9 and electricity 0.12 per kWh are unfavourable; carbon pricing or lower electricity prices change this	Hourly simulation of heat recovery, storage and tariffs
Emissions use average grid intensity with a linear decline; no refrigerant leakage; no embodied carbon of pipe	Marginal factors and embodied carbon would change abatement costs modestly	Regional marginal factors (Siler-Evans et al., 2012); EPD data for pipe
Metamodel and screening rule reproduce the model, not reality	The rule (accuracy 71% against a 57% base rate) is weak; the decision depends on interactions that a shallow tree cannot express	Re-estimate on a portfolio of campuses with recorded decisions and outcomes
Evaluation is artificial (design-science sense)	Framework outputs are shown to be informative on a model whose truth is known; usefulness in practice is untested	Naturalistic evaluation on a campus with metered data, quotes and a recorded decision

Conclusion

This article designed a data-driven decision-analytics framework for the choice between keeping a campus steam system and converting it to hot water, and evaluated it on a transparent parametric model of a synthetic campus in four climates under six strategies and 32 uncertain inputs. The framework connects a calibrated distribution-loss model, a network model with trap, condensate, flash and blowdown balances, an age-dependent failure hazard, probabilistic life-cycle costing with phasing and parallel operation, global sensitivity analysis, a metamodel with a screening rule, and measurement-and-verification feedback. The documented conversions that motivate such decisions were verified against their primary sources; several figures in circulation, including two institutional claims, could not be.

On the model, steam distribution loses 20–35% of plant output and delivers 49–62% of fuel as heat against 87–88% for hot water, so conversion cuts gas use by 29–37% and thirty-year emissions by 26–33%, or 46–50% with heat pumps. Its life-cycle cost advantage is conditional: fast conversion is least-cost in 33% of draws in the warm climate and 78% in the cold one, rising to 72–98% with gas at 15 per MMBtu and to 90–100% with a carbon price of 190 per tonne or a small retrofit scope, and falling to 7–46% if the mains are 20 years younger; the maintenance programme pays in 86–89% of draws and should come first; a nine-year programme costs 15–18 per m² more than a three-year one; continuous trap monitoring beats periodic surveys at every gas price; and the plant-minus-meter balance identifies the total distribution loss to within a percentage point. The discount rate, retrofit scope, gas price and asset age explain most of the variance, and the value of perfect information of 4–7 per m² says that the surveys which resolve them are worth commissioning.

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