

Article

Algorithms for Smart-City Waste Infrastructure: A Two-Stage Stochastic MILP with Endogenous Waste-to-Energy Sizing and Shadow-Price Policy Design for Metropolitan Athens

Athanasios S. Dagoumas

School of Economics, Business and International Studies, University of Piraeus, 150 Androutsou St., 18534 Piraeus, Greece; dagoumas@unipi.gr

Abstract

Decarbonising municipal solid waste (MSW) is a defining algorithmic challenge for smart cities: waste-to-energy (WtE), composting and material-recovery investments must be committed years ahead under deep uncertainty about household source-separation uptake and the governing policy instruments (landfill taxes, carbon prices, compost subsidies). We present a two-stage stochastic mixed-integer linear programming (MILP) framework, applied to the Attica region of Greece (Athens; 5122 t/day MSW) and calibrated to confirmed 2024 weighbridge data. The contribution is an integration strategy rather than a new technique: endogenous WtE capacity sizing (Special Ordered Sets of Type 2 (SOS2) piecewise-linear cost, economies-of-scale exponent 0.85), the bilinear capacity–build coupling linearised exactly by McCormick envelopes (one factor being binary), and Pigouvian shadow-price recovery of the optimal policy instruments are combined in a single-shot, gap-bounded MILP and embedded in a 10,000-run Latin-hypercube Monte Carlo layer over 12 parameters with Spearman sensitivity indices. The individual components are established; their joint formulation is, to our knowledge, new. The pipeline solves 10,415 MILP instances. Three results are policy-relevant: investment is robust to rollout uncertainty ($VSS \approx \text{€}0$; $EVPI \approx \text{€}5.4 \text{ M}$, 0.15%); the carbon price alone explains ~80% of cost variance ($\rho = +0.891$); and, under the model's calibration, the implied Pigouvian-optimal landfill tax (€1100–3300/t) indicates a binding landfill cap is needed to secure diversion. The framework transfers to any metropolitan MSW system facing decarbonisation and circular-economy mandates.

Keywords: stochastic programming; mixed-integer linear programming; waste-to-energy; SOS2 piecewise linearisation; McCormick envelopes; Monte Carlo simulation; smart cities; municipal solid waste; Pigouvian taxation; circular economy

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1. Introduction

Smart cities increasingly rely on algorithmic decision support to allocate scarce physical infrastructure efficiently and to lower their environmental footprint. Few urban sub-systems illustrate this better than municipal solid waste (MSW): the transition from landfill-dominated disposal to integrated resource recovery requires coordinated, capital-intensive and largely irreversible investment in multiple treatment facilities over multi-year horizons. In the European Union the transition is driven by binding legislation—the Waste Framework Directive 2018/851 [1] mandates 55% recycling by 2025 and 65% by

2035, the Landfill Directive 2018/850 [2] restricts landfilling to 10% of municipal waste by 2035, and member states translate these targets into facility-level investment portfolios. The Attica region of Greece—home to ~40% of the national population and generating approximately 5122 t/day of MSW [3]—faces a particularly acute version of this challenge.

Three features make the Attica problem a demanding algorithmic test case rather than a routine facility-location exercise. First, the dominant uncertainty is the speed of the household source-separation rollout mandated by Law 4819/2021 [4]: in 2024 only 55 t/day of source-separated biowaste and 51 t/day of recyclables were collected, against PESDA 2025 targets an order of magnitude larger [5]. Second, the regulatory timeline imposes binding milestones—the landfill cap tightens from 95% (2024) to 10% (2030 onward), the diversion target ramps to 65% by 2035, and the Fyli landfill levy escalates from €30/t (2024) to €68/t (2035)—so investment decisions are constraint-driven rather than discretionary. Third, the policy environment is in flux: the Greek government (YPEN) mandates two WtE plants from 2030 under its 2025 SMPE plan [6], the Attica Regional Council voted unanimously against all WtE in September 2025, and the EU is considering extending its Emissions Trading System (ETS) to municipal waste incineration from 2028. The European Court of Auditors Special Report 23/2025 [7] explicitly audits Greece as one of four member states failing EU waste targets over 2014–2024, with a 2022 recycling rate of only 17% against an EU-27 average of 49%.

These three features interact: the optimal infrastructure portfolio depends jointly on rollout speed, on economies of scale in plant sizing, and on the policy instruments that price externalities. No single deployed model captures all three. A framework that can jointly optimise infrastructure under rollout uncertainty, size facilities endogenously, evaluate policy-instrument effectiveness and identify robust investment portfolios is therefore an operational necessity for the responsible authorities (EDSNA, YPEN), not merely an academic exercise.

Beyond the use of optimisation, the problem is a smart-city problem in a concrete operational sense. The model is calibrated to—and is designed to be re-run against—the digital data infrastructure that Attica’s authorities already operate: networked weighbridge records at every transfer and treatment facility [3], per-zone source-separation participation generated by the three-bin collection programme, and the regional digital waste registry maintained under Law 4819/2021 [4]. These data streams turn infrastructure planning from a one-off study into a repeatable, data-driven decision loop: as monitored separation rates and weighbridge tonnages are updated, the optimisation can be re-solved to revise the investment timing and operational routing. What makes the problem ‘smart’ is therefore not the algorithm in isolation but the closed loop between sensed urban data (waste flows, citizen participation, facility utilisation) and the capital-allocation and policy decisions the algorithm informs—the same sense in which smart-grid or smart-mobility planning is considered ‘smart’ [8]. Section 6.3 returns to how the model’s shadow-price outputs feed back into this loop as policy signals.

Contributions

This paper develops and applies a two-stage stochastic MILP for metropolitan MSW investment planning. Stage 1 fixes here-and-now investment timing and WtE capacity; Stage 2 adapts operational waste routing to the realised rollout scenario. The contributions are primarily algorithmic and are summarised as follows:

(C1) Endogenous capacity sizing via SOS2 piecewise linearisation. Whereas conventional MSW MILPs treat WtE as a binary build/no-build decision at a fixed capacity, we make capacity a continuous decision variable governed by a concave annualised-cost function $CAPEX_ann(cap) = capex_fixed + capex_unit \cdot cap^{0.85}$. The concave function is linearised exactly at its breakpoints by a Special Ordered Set of Type 2 (SOS2), letting the solver trade economies of scale against stranded-asset risk. The novelty is not the SOS2 device of Beale and Tomlin [9] but its use to size WtE endogenously inside a stochastic MSW MILP, where it must coexist with scenario-dependent routing.

(C2) Exact linearisation of the capacity–build coupling via McCormick envelopes. Because activated capacity is the bilinear product of the continuous capacity variable and the binary build variable, and similarly for annualised CAPEX, we introduce auxiliary variables bounded by McCormick envelopes, keeping the model a single-shot MILP solvable to a guaranteed gap. Because one factor of this product is binary, the McCormick envelope [10] is exact rather than a relaxation (derivation in Section 4.4); the contribution is that this keeps the scenario-extended model a single MILP.

(C3) Shadow-price policy design. A social-welfare variant replaces private cost with real resource cost plus monetised GHG damage minus compost benefit; the Pigouvian-optimal landfill tax and diversion penalty are then recovered directly from the shadow prices of the binding regulatory constraints. The contribution is the recovery of these instruments from the dual of a calibrated facility-level stochastic MILP, which no prior MSW study reports.

(C4) A 10,000-run Latin-hypercube Monte-Carlo layer over 12 uncertain parameters, with Spearman rank-correlation sensitivity indices and formal computation of the Value of the Stochastic Solution (VSS) and the Expected Value of Perfect Information (EVPI). The complete pipeline solves 10,415 MILP instances on a standard workstation in ~1.9 h, making it suitable for interactive use by a waste authority. The contribution is the integration of distribution-free global sensitivity at scale (12 parameters, 10,000 full MILP solves) with the stochastic-investment model. Every component technique is mature; the paper’s contribution is their joint, single-shot integration and calibration to a real metropolitan system.

The framework is demonstrated on a real metropolitan system calibrated to confirmed 2024 operational data rather than synthetic instances, and yields three decision-grade findings (Section 5): investment is robust to rollout uncertainty, the carbon price dominates cost uncertainty, and—under the model’s assumptions—a binding landfill cap is necessary to secure the diversion outcome. The remainder of the paper is organised as follows. Section 2 reviews related work and demonstrates why existing methods cannot be adapted to the present problem. Section 3 describes the study area, institutional context and data. Section 4 presents the complete mathematical model and the solution algorithm. Section 5 reports results, Section 6 discusses implications, and Section 7 concludes; Appendices A and B provide the parameter source audit and the scalability analysis.

2. Related Work and Research Gap

Investment planning for waste-to-energy and broader MSW systems under uncertainty is a mature and active field. Rather than asserting novelty, this section reviews the four method families that the Attica problem touches—stochastic MSW programming, endogenous capacity-sizing algorithms, optimal environmental-policy instruments, and global sensitivity analysis—and shows, for each, the specific structural reason why the best available method cannot be adapted to the present problem with only modest modification (Section 2.5).

2.1. Stochastic Programming for MSW and WtE Systems

Two-stage stochastic programming for waste management was formalised by Birge and Louveaux [11], who showed that the Value of the Stochastic Solution can be large when uncertainty is high. In the MSW domain, Huang, Sae-Lim, Liu and Chen [12] pioneered interval-parameter fuzzy-stochastic programming that handles parameter uncertainty through bounded intervals rather than discrete scenarios, and Xu, Huang, Qin and Cao [13] developed a stochastic robust chance-constrained model permitting controlled violation of waste-management targets under extreme scenarios. More recently, Ghasemi, Ali, Abolghasemian, Ahmadi Malakoot and Pourghader Chobar [14] applied a stochastic, ϵ -constraint-based closed-loop supply-chain model to end-of-life solar-photovoltaic recovery, confirming that explicit uncertainty modelling materially reshapes optimal network and capacity design. Madansky [15] established the inequalities that underpin the EVPI bound used here. The common thread

of this literature is that uncertainty is assumed to dominate the decision; none of these models is calibrated to confirmed operational weighbridge data from a major EU metropolitan system, and none reports an EVPI that quantifies the value of resolving rollout uncertainty before committing capital.

Beyond scenario-based stochastic programming, two adjacent algorithmic traditions bear on the present problem. Robust optimisation replaces the probability distribution with an uncertainty set and optimises against the worst case [16]; it is attractive when distributions are unknown, but here the rollout scenarios and their plausibilities are reasonably characterised and, as Appendix B shows, the worst-case rollout yields the same first-stage decision, so a robust counterpart adds little. Decomposition methods—the L-shaped/Benders method [17] and progressive hedging [18]—make large scenario trees tractable by exploiting their block structure, and become necessary only at scenario counts far above those required here (Appendix B). The problem also belongs to the stochastic facility-location family [19], from which it inherits the capacitated, here-and-now siting structure while adding endogenous continuous sizing and dual-based policy extraction.

2.2. Endogenous Capacity Sizing and Piecewise-Linear Cost Algorithms

In deployed MSW models, capacity is typically fixed: Costi, Minciardi, Robba, Rovatti and Sacile [20] and Mavrotas, Gakis, Skoulaxinou, Katsouros and Georgopoulou [21] select among predetermined facility sizes through binary decisions. Continuous sizing with economies of scale is, however, a solved problem in the optimisation literature: Beale and Tomlin [9] introduced special ordered sets for non-convex piecewise functions, Martin [22] surveys exact piecewise-linear formulations, and McCormick [10] provides the envelope relaxation for bilinear products. These techniques are standard in energy-systems modelling but, to our knowledge, have not been combined and applied to endogenous WtE plant sizing in a metropolitan MSW MILP. The gap is not the existence of the technique but its absence from this application class.

2.3. Optimal Environmental-Policy Instruments

The Pigouvian tradition [23] holds that the optimal tax on a polluting activity equals marginal social damage; Baumol and Oates [24] extended this to second-best settings, and Weitzman [25] showed that quantity instruments (caps, standards) dominate price instruments (taxes) when the marginal-damage curve is steep relative to the marginal-abatement-cost curve. Whether that condition holds for a specific MSW system is an empirical question answerable only by computing the relevant shadow prices under realistic data. Landfill taxes are known to incentivise recycling and energy recovery [26], and the EEA notes that Greece's landfill fee is far below those of other member states and has not created recycling incentives [27]. Yet no published study derives the Pigouvian-optimal landfill-tax trajectory for a real metropolitan system from the shadow prices of a facility-level stochastic MILP—the survey of Ghiani, Laganà, Manni, Musmanno and Vigo [28] explicitly lists policy-instrument design as an underexplored area in operations research for solid waste.

2.4. Global Sensitivity Analysis in Facility Planning

Sensitivity analysis in MSW optimisation has typically been limited to one-at-a-time variation or small factorial designs [29,30]. Latin Hypercube Sampling, introduced by McKay, Beckman and Conover [31], provides efficient coverage of high-dimensional parameter spaces, and the distribution-free rank-correlation approach of Iman and Conover [32] gives a non-parametric monotonic-sensitivity measure suited to MILP outputs with threshold effects; Saltelli, Ratto, Andres, Campolongo, Cariboni, Gatelli, Saisana and Tarantola [29] codify good practice, and Burmaster and Anderson [33] recommend $\geq 10,000$ samples for reliable tail esti-

mation. These methods are routine in risk analysis but have rarely been applied at scale (>5 uncertain parameters) to MSW facility-investment models.

2.5. Why Existing Methods Cannot Be Adapted Directly

The four families above are individually mature, but each fails on a structural feature of the Attica problem that cannot be removed by modest adaptation:

Stochastic-MSW models [12–14] fix capacity exogenously; adding rollout scenarios to them would still leave plant size predetermined, so they cannot answer the central question—what WtE capacity is optimal—and cannot exhibit the scale-economy/stranded-asset trade-off that drives the result.

Capacity-sizing formulations [9,10,22] are deterministic; appending scenarios to a SOS2/McCormick model introduces a bilinear capacity $\times$ build term per scenario that, left unlinearised, makes the program non-convex and intractable—the contribution is the joint linearisation that keeps it a single MILP.

Policy-instrument theory [23–25] is analytic and system-agnostic; it prescribes that the optimal tax equals marginal damage but provides no marginal-abatement-cost curve for a specific facility network. Only the dual of a calibrated MILP supplies that curve, which is why the optimal tax cannot be read off existing partial-equilibrium models.

Global-sensitivity methods [29–32] presuppose a fast-to-evaluate model; here, each sample is a full MILP solve, so naïve Monte Carlo is prohibitive without the warm-started, gap-bounded solve pipeline of Section 4.9.

Consequently, the Attica problem requires the four method families to be combined in a single formulation—stochastic scenarios, endogenous SOS2 sizing with McCormick linearisation, shadow-price policy extraction, and a MILP-aware Monte-Carlo layer—rather than any one of them applied or lightly extended. That combination, calibrated to confirmed operational data, is the contribution of this paper.

We stress that none of the four method families is claimed as novel in itself: two-stage stochastic programming, SOS2, McCormick envelopes and LHS are textbook techniques. What is new is that the structural features of the Attica problem force them into a single formulation—removing any one (for example, fixing capacity, or analysing policy separately) makes the central question unanswerable—and that the integrated model is calibrated to confirmed operational data rather than synthetic instances. Table 1 positions the present model against representative prior MSW/WtE optimisation studies.

Table 1. Positioning against representative prior MSW/WtE optimisation studies.

Study	Uncertainty	Capacity	Econ. of Scale	Bilinear Linearisation	Policy Output	GSA (#Params)	Calibration
Huang et al. 2001 [12]	interval-fuzzy	fixed	no	—	none	OAT	synthetic
Xu et al. 2009 [13]	chance-constrained	fixed	no	—	none	OAT	synthetic
Costi et al. 2004 [20]	deterministic	discrete sizes	no	—	none	OAT	regional
Mavrotas et al. 2015 [21]	deterministic	discrete sizes	no	—	external cost	small factorial	regional
Ghasemi et al. 2025 [14]	stochastic (ϵ -constraint)	fixed	no	—	none	OAT	case study
This paper	2-stage stochastic 10k LHS	+ endogenous (continuous)	yes (0.85)	McCormick (exact)	Pigouvian dual	12	confirmed 2024 weighbridge

No prior model occupies the bottom row: each fixes at least one of {capacity, uncertainty, policy output}, which is precisely the structural barrier Section 2.5 describes.

2.6. The Integration as an Algorithmic Contribution

The four method families combined here—two-stage stochastic programming [11], SOS2 piecewise-linear cost modelling [9], McCormick envelopes [10], and Latin-hypercube sampling [31]—are individually mature, and we claim novelty for none of them in isolation. The contribution of this paper is a formulation result: we show that the three modelling requirements a deployable metropolitan WtE model must satisfy simultaneously—endogenous capacity sizing with economies of scale, scenario-based treatment of rollout uncertainty, and recovery of policy instruments—can be met within a single, exactly-linearised, gap-bounded mixed-integer linear program, rather than a non-convex program or an iterative sequence of subproblems.

The technical crux is that endogenous sizing and uncertainty interact. Representing economies of scale through an SOS2 piecewise-linear CAPEX curve makes the installed capacity a decision variable; once rollout scenarios are introduced, this capacity multiplies the scenario-dependent build and utilisation decisions, producing bilinear terms that a naïve scenario extension of a fixed-capacity model would render non-convex. As shown in Section 4.4, these bilinear terms are of the binary $\times$ continuous type, for which the McCormick envelope is not a relaxation but is exact at every integer-feasible point, so the coupling is linearised without loss and the deterministic-equivalent problem remains a single MILP solvable to a certified optimality gap.

This is an algorithmic statement, not merely an application, in three respects. First, it is a tractability result for a transferable problem class—endogenous-capacity stochastic facility siting under scale economies—-independent of the waste-management context. Second, the exactness of the linearisation is a provable structural property of binary $\times$ continuous products (Section 4.4), so the integration is principled rather than a heuristic assembly. Third, the same formulation is designed so that its linear-programming dual yields the shadow-price (Pigouvian) policy instruments directly, an output none of the component techniques provides individually. Consistent with the scope of this journal, the transferable object of the paper is therefore this formulation-and-linearisation recipe together with its empirically characterised scaling behaviour (Appendix B), with the Metropolitan Athens system serving as the calibrated testbed on which it is demonstrated.

3. Study Area, Institutional Context and Data

3.1. The Attica MSW System

The Attica region encompasses the broader Athens metropolitan area and comprises eight waste-generation zones (KEN, VOR, NOT, DYT, PIR, NSI, DYA, ANT), four Strategic Material Stations (SMAs), and eleven treatment and disposal facilities. The system topology, zone-level generation profiles and facility specifications are calibrated to the PESDA regional plan [5] and confirmed 2024 EDSNA weighbridge records [3]; total daily generation in 2024 was 5122 t/day. The eleven candidate facilities are EMAK (742 t/day net material-recovery facility, always operational); six MAA composting/MRF parks (MAA_KEN 863, MAA_PIR 329, MAA_VOR 356, MAA_DYT 548, MAA_NOT 219, MAA_ANT 164 t/day); MEVA (1137 t/day mechanical-biological treatment with anaerobic digestion); WTE_ATT (endogenous capacity, max 1200 t/day); WTE_ATT2 (endogenous capacity, max 700 t/day); and the Fyli landfill XYTA_F (5230 t/day net). Cost parameters are calibrated from Eunomia EU benchmarks [34], WRAP gate-fee surveys [35], Greek-specific costs [36], CEWEP WtE benchmarks [37,38], IPCC emission factors [39], the EEA Greece inventory [40], Eurostat EU waste-infrastructure cost data [41] (used for the SMA fixed-cost benchmark), the PESDA regional plan [5], and confirmed 2024 EDSNA operational files [3]. The complete parameter set—every value with its source, uncertainty range and calibration procedure—is provided in the Supplementary Materials (Supplementary

Files S1–S5) and in the machine-readable reproducibility file 01_parameters.csv, and is classified by source quality in Appendix A (Table A1); the twelve parameters carried into the uncertainty analysis are described in Section 4.8.

The WtE capacity bounds are not free parameters but follow the institutional plan and the system's residual mass balance. The two-plant configuration and the upper bounds ($WtE_ATT \leq 1200$ t/day, $WtE_ATT2 \leq 700$ t/day; combined ≤ 1900 t/day) reproduce the indicative plant sizes of the YPEN/PESDA SMPE plan [5,6] and are consistent with the residual (non-recyclable, non-compostable) tonnage that remains once the 2030 diversion targets are met at the confirmed 2024 generation level. The lower bounds (300/200 t/day) reflect the smallest economically viable moving-grate combustion train reported in the CEWEP WtE benchmarks [37,38]; below them, specific CAPEX rises steeply and a dedicated plant is not justified. Because these bounds frame the central sizing result, the optimal capacity is reported throughout against them, and the CAPEX-unit cost that scales them is itself treated as uncertain in the Monte-Carlo analysis (Section 4.8).

3.2. Source-Separation Rollout Uncertainty

The two-stage structure (Figure 1) commits Stage-1 investment before the rollout scenario is revealed and adapts Stage-2 routing afterwards. The critical uncertainty is the speed of the three-bin source-separation rollout mandated by Law 4819/2021 [4]. Four rollout scenarios are defined (Table 2, Figure 2), calibrated to the 2024 actual baseline and PESDA 2025 targets, and entering the model as the scenario-dependent generation profile $gen(i,w,t,s) = gen24(i,w) + \alpha(t,s) \cdot (gen25(i,w) - gen24(i,w))$.

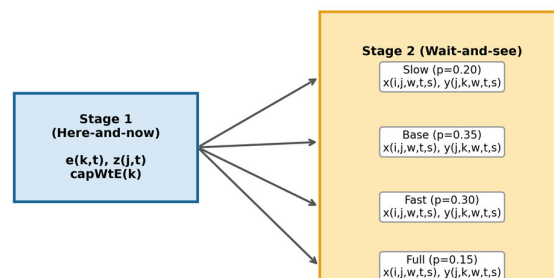


Figure 1. Two-stage stochastic MILP structure: Stage-1 (here-and-now) investment decisions are scenario-independent; Stage-2 (wait-and-see) operational flows adapt to the realised rollout scenario.

Table 2. Rollout scenario definitions.

Scenario	Prob.	α (2027)	α (2030)	Description
Slow	0.20	0.150	0.600	Delayed; compliance by 2032
Base	0.35	0.350	1.000	PESDA planned trajectory
Fast	0.30	0.600	1.000	Accelerated Law 4819/2021
Full	0.15	0.850	1.000	Near-complete by 2027

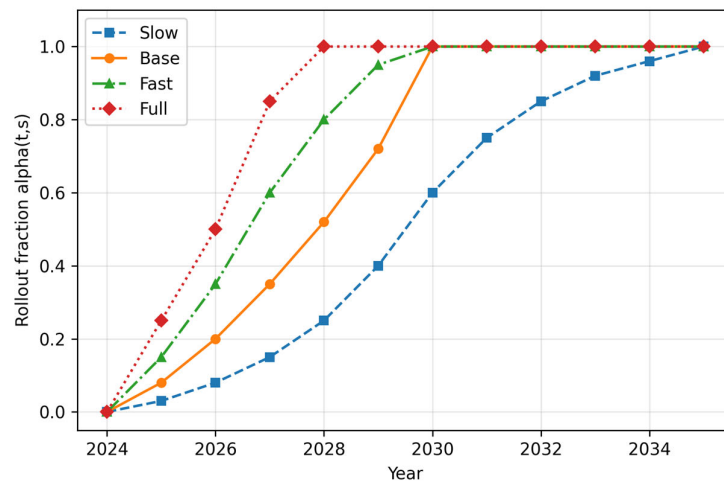


Figure 2. Source-separation rollout trajectories $\alpha(t,s)$ for the four scenarios over 2024–2035 (no other quantities are plotted in this figure).

The four rollout probabilities (slow 0.20, base 0.35, fast 0.30, full 0.15) are a structured prior: central mass is placed on the PESDA-planned trajectory and the remainder distributed by the judged plausibility of faster versus slower compliance given the 2024 baseline shortfall; they are not estimated frequencies. Because a subjective prior should not drive conclusions, a probability-robustness experiment (Table 3) re-solves the stochastic and EVPI problems under equal weights, a pessimistic (slow-weighted) prior, an optimistic (fast/full-weighted) prior, and 2000 Dirichlet draws over the probability simplex. The Stage-1 capacity decision—WTE_ATT at 1200 t/day and WTE_ATT2 at 700 t/day—is invariant across all four priors; expected NPV varies within a narrow €2764–2776 M band, the EVPI stays within solver tolerance of zero for every prior, and over the 2000 Dirichlet draws expected NPV is €2767 M $\pm$ €2.6 M ($\pm 0.4\%$). The first-stage decision is therefore insensitive to the choice of scenario prior.

Table 3. Probability-robustness experiment (stochastic solve, baseline regulatory regime).

Prior (Slow/Base/Fast/Full)	Expected NPV (€ M)	WTE_ATT (t/day)	WTE_ATT2 (t/day)	EVPI (€ M)
Baseline 0.20/0.35/0.30/0.15	2767	1200	700	≈ 0
Equal 0.25/0.25/0.25/0.25	2771	1200	700	≈ 0
Pessimistic 0.55/0.25/0.15/0.05	2776	1200	700	≈ 0
Optimistic 0.05/0.15/0.40/0.40	2764	1200	700	≈ 0
Dirichlet (2000 draws)	2767 $\pm$ 2.6	1200	700	—

3.3. Policy Instrument Ranges

Three policy instruments are treated as uncertain and scanned parametrically (Table 4): the landfill tax, the carbon price (anticipating EU ETS extension to waste incineration), and the compost price.

Table 4. Policy instrument ranges.

Instrument	Base	Range	Source
Landfill tax (€/t)	30	20–150	Law 4819/2021; EU range
Carbon price (€/tCO ₂)	0	0–200	EU ETS; 2030 projection
Compost price (€/t)	0	0–50	EU compost market

4. The Optimisation Model

This section presents the complete, self-contained formulation in the main text, as is appropriate for an algorithms-focused contribution. Section 4.1 defines sets, parameters and variables; Section 4.2 the two-stage stochastic objective; Section 4.3 the operational and regulatory constraints; Sections 4.4–4.6 the three algorithmic devices (endogenous SOS2 sizing, McCormick linearisation, stranded-asset penalty); Section 4.7 the social-welfare/shadow-price variant; Section 4.8 the Monte-Carlo design; and Section 4.9 the solution algorithm and implementation. To keep the main text focused, the full parameter-by-parameter audit is summarised in Appendix A and given in detail in the Supplementary Materials, and the scalability analysis and comparison with alternative methods are placed in Appendix B.

4.1. Sets, Parameters and Decision Variables

Key parameters (full audit in Appendix A and the Supplementary Materials) include the discount factor $df(t)$ with rate 5%; the diversion target $divTgt(t)$ ramping 0.22→0.65 (WFD 2018/851); the landfill cap $lfCap(t)$ tightening 0.95→0.10 (Law 4819/2021); the time-varying levy $lfLevy(t)$ €30→€68/t; transport costs $cIJ(i,j)$, $cJK(j,k)$; processing costs $cProc(k,w)$; facility capacities $capFac(k)$, $expandCap(k)$; GHG factors $ghgFac(k,w)$ from IPCC 2006 Vol.5 [39]; scenario rollout fractions $\alpha(t,s)$; the EMAK residual-reject fractions $rEMAK(w)$; the scenario total generation $totalGen(t,s) = \sum_{\{i,w\}} gen(i,w,t,s)$; the compost output $compost(t,s) = 0.276 \cdot \sum_j y(j, MEVA, BIO, t, s) + 0.110 \cdot \sum_{\{j,w\}} y(j, EMAK, w, t, s)$; and the WtE capacity bounds $capWtE_max$ (1200/700 t/day) and $capWtE_min$ (300/200 t/day). The sets and subsets are listed in Table 5 and the decision variables in Table 6.

Table 5. Sets and subsets.

Symbol	Description	Elements/Cardinality
I	Waste-generation zones	KEN, VOR, NOT, DYT, PIR, NSI, DYA, ANT ($ I = 8$)
J	Transfer stations (SMAs)	SMA_SCH, SMA_ELA, SMA_ANL, SMA_EAT ($ J = 4$)
K	Treatment/disposal facilities	EMAK, $6 \times$ MAA, MEVA, WTE_ATT, WTE_ATT2, XYTA_F ($ K = 11$)
W	Waste streams	BIO, PLA, PAP, GLS, MET, GRN, RES ($ W = 7$)
T	Annual investment periods	p2024...p2035 ($ T = 12$)
S	Rollout scenarios	slow, base, fast, full ($ S = 4$)
$K_wte \subseteq K$	WtE facilities	WTE_ATT, WTE_ATT2
$K_new \subseteq K$	Facilities needing a build decision	$6 \times$ MAA, MEVA, WTE_ATT, WTE_ATT2 ($ K_new = 9$)
NB	SOS2 breakpoints	bp1...bp5 ($ NB = 5$)

Table 6. Decision variables.

Variable	Stage/Type	Domain	Description
$e(k,t)$	1/binary	$K_new \times T$	1 if facility k operational in period t (here-and-now)
$z(j,t)$	1/binary	$J \times T$	1 if SMA j open in period t
$capWtE(k)$	1/continuous	K_wte	Endogenous WtE capacity (t/day)
$\lambda(k,n)$	1/SOS2	$K_wte \times NB$	SOS2 weights on capacity breakpoints
$x(i,j,w,t,s)$	2/continuous	$I \times J \times W \times T \times S$	Flow zone→SMA (t/day)
$y(j,k,w,t,s)$	2/continuous	$J \times K \times W \times T \times S$	Flow SMA→facility (t/day)
$capWtE_act(k,t)$	aux/continuous	$K_wte \times T$	McCormick auxiliary for $capWtE \times e$
$capexWtE_act(k,t)$	aux/continuous	$K_wte \times T$	McCormick auxiliary for $capexWtE_ann \times e$
$slack_util(k,t,s)$	aux/continuous	$K_wte \times T \times S$	WtE under-utilisation slack

Three groups of variables warrant explicit comment, because they carry the algorithmic content of the formulation. (i) The SOS2 weights $\lambda(k,n)$ are convex-combination coefficients that select a point on the piecewise-linear CAPEX curve (Section 4.5); at most two

adjacent weights may be non-zero, so they interpolate between neighbouring capacity breakpoints. (ii) The activated-capacity auxiliaries $\text{capWtE_act}(k,t)$ and $\text{capexWtE_act}(k,t)$ hold, respectively, the WtE capacity and its annualised CAPEX only in periods when the plant is built ($e(k,t) = 1$), and zero otherwise; they linearise the binary $\times$ continuous products $\text{capWtE} \cdot e$ and $\text{capexWtE_ann} \cdot e$ exactly (Section 4.4). (iii) The slack variable $\text{slack_util}(k,t,s)$ measures any throughput shortfall below the target utilisation of activated capacity and carries the stranded-asset penalty (Section 4.6). For notational consistency we distinguish the modelled landfill levy $\text{lfLevy}(t)$ (a fiscal parameter in the cost objective) from the Pigouvian-optimal landfill tax $\text{lfTax}^*(t,s)$ recovered from the dual (Section 4.7), and the private-cost policy parameters (co2Price , cmpPrice) from their social-welfare counterparts, the social cost of carbon (SCC) and the social value of compost (SVC).

4.2. Two-Stage Stochastic Objective

The primary objective minimises the probability-weighted net present value (NPV) of total system cost across the four rollout scenarios:

$$\min \text{NPV_total} = \sum_{s \in S} \text{prob}(s) \cdot \text{NPV}_s(s) \quad (1)$$

$$\text{NPV}_s(s) = \sum_{t \in T} \text{df}(t) \cdot C(t,s) \quad (2)$$

The period cost $C(t,s)$ decomposes into eleven components—primary collection, zone $\rightarrow$ SMA and SMA $\rightarrow$ facility transport plus processing, the landfill levy, the carbon tax, a compost revenue credit, fixed SMA cost, annualised non-WtE CAPEX, the endogenous (linearised) WtE CAPEX, the fixed EMAK maintenance term, and the stranded-asset penalty:

$$C(t,s) = 365 \cdot \sum_{i,w} \text{cPrimColl}(i) \cdot \text{gen}(i,w,t,s) + 365 \cdot \sum_{i,j,w} \text{cIJ}(i,j) \cdot x(i,j,w,t,s) \quad (3a)$$

$$+ 365 \cdot \sum_{j,k,w} [\text{cJK}(j,k) + \text{cProc}(k,w)] \cdot y(j,k,w,t,s) + 365 \cdot \text{lfLevy}(t) \cdot \sum_{j,w} y(j,XYTA_F,w,t,s) \quad (3b)$$

$$+ 365 \cdot \text{co2Price} \cdot \sum_{j,k,w} \text{ghgFac}(k,w) \cdot y(j,k,w,t,s) - 365 \cdot \text{cmpPrice} \cdot [0.276 \cdot \sum_j y(j,MEVA,BIO,t,s) + 0.110 \cdot \sum_{j,w} y(j,EMAK,w,t,s)] \quad (3c)$$

$$+ \sum_j \text{fixedSMA}(j) \cdot z(j,t) + \sum_{\{k \notin K_wte\}} \text{capexAnn}(k,t) \cdot e(k,t) + \sum_{\{k \in K_wte\}} \text{capexWtE_act}(k,t) \quad (3d)$$

$$+ \text{capexEMAK_annual} + \text{strandedPen} \cdot \sum_{\{k \in K_wte\}} \text{slack_util}(k,t,s)$$

Investment timing, build order and WtE capacity are placed in Stage 1 because they are here-and-now, irreversible commitments that must be made before the rollout is observed and cannot be revised annually once built; irreversibility is enforced by the monotonicity constraint (Equation (11)). Operational routing is the only genuinely recourse-adaptable decision and is therefore Stage 2. A fully multistage formulation would instead let capacity be revised at each period as uncertainty unfolds; this is more realistic for staged build-out but multiplies the scenario tree with each stage and is valuable only when intermediate information is decision-relevant. Here the near-zero EVPI (Section 5.3) shows it would add little, because the optimal capacity is a robust corner solution (Section 5.9) that does not depend on when uncertainty resolves; a multistage or rolling-horizon extension is noted as future work (Section 6.6).

4.3. Operational and Regulatory Constraints

Mass balance requires that all waste generated in a zone be dispatched to the SMA network, and flow conservation that all SMA inflow be routed onward to treatment (both carry the scenario index s):

$$\sum_{j \in J} x(i,j,w,t,s) = \text{gen}(i,w,t,s) \quad \forall i \in I, w \in W, t \in T, s \in S \quad (4)$$

$$\sum_{i \in I} x(i,j,w,t,s) = \sum_{k \in K} y(j,k,w,t,s) \quad \forall j \in J, w \in W, t \in T, s \in S \quad (5)$$

SMA open/closed logic and throughput capacity:

$$\sum_{w \in W} x(i,j,w,t,s) \leq \text{bigM} \cdot z(j,t) \quad \forall i \in I, j \in J, t \in T, s \in S \quad (6)$$

$$\sum_{i \in I, w \in W} x(i,j,w,t,s) \leq \text{capSMAeff}(j) \cdot z(j,t) \quad \forall j \in J, t \in T, s \in S \quad (7)$$

Non-WtE facility throughput is bounded by base plus investment-unlocked expansion capacity (WtE facilities are handled separately in Section 4.4):

$$\sum_{j \in J, w \in W} y(j,k,w,t,s) \leq \text{capFac}(k) + \text{expandCap}(k) \cdot e(k,t) \quad \forall k \in K \setminus K_{\text{wte}}, t \in T, s \in S \quad (8)$$

The EU WFD true-diversion target and the Law 4819/2021 landfill cap are the binding regulatory constraints; investment is irreversible (monotone):

$$\sum_{j,w} y(j,XYTA_F,w,t,s) + \sum_{j,w} [r\text{EMAK}(w) - 0.011] \cdot y(j,\text{EMAK},w,t,s) \leq [1 - \text{divTgt}(t)] \cdot \text{totalGen}(t,s) \quad \forall t,s \quad (9)$$

$$\sum_{j \in J, w \in W} y(j,XYTA_F,w,t,s) \leq \text{lfCap}(t) \cdot \text{totalGen}(t,s) \quad \forall t \in T, s \in S \quad (10)$$

$$e(k,t) \leq e(k,t+1) \quad \forall k \in K_{\text{new}}, t \in T \setminus \{t_{\text{last}}\} \quad (11)$$

Technology-specific routing constraints (PESDA specifications) prohibit infeasible facility-stream assignments: source-separated recyclables cannot be landfilled; EMAK rejects pure residual; BIO cannot be sent directly to Fyli; WTE_ATT2 accepts only non-recyclable streams; and MEVA, an anaerobic-digestion plant, accepts only the BIO and GRN organic fractions. These are imposed as $y(j,k,w,t,s) = 0$ on the prohibited (k,w) pairs.

4.4. Endogenous WtE Capacity with McCormick Linearisation

For WtE facilities the throughput bound uses an activated-capacity variable $\text{capWtE_act}(k,t)$ that equals the bilinear product $\text{capWtE}(k) \cdot e(k,t)$. Because the product of a continuous and a binary variable is nonlinear, it is replaced exactly by its McCormick envelope (Equation (13a–c)), which forces $\text{capWtE_act} = \text{capWtE}$ when $e = 1$ and $\text{capWtE_act} = 0$ when $e = 0$:

$$\sum_{j \in J, w \in W} y(j,k,w,t,s) \leq \text{capWtE_act}(k,t) \quad \forall k \in K_{\text{wte}}, t \in T, s \in S \quad (12)$$

$$\text{capWtE_act}(k,t) \leq \text{capWtE_max}(k) \cdot e(k,t) \quad (13a)$$

$$\text{capWtE_act}(k,t) \leq \text{capWtE}(k) \quad (13b)$$

$$\text{capWtE_act}(k,t) \geq \text{capWtE}(k) - \text{capWtE_max}(k) \cdot [1 - e(k,t)] \quad (13c)$$

The annualised-CAPEX product $\text{capexWtE_ann}(k) \cdot e(k,t)$ is linearised identically, with big-M cost bound M_{cost} :

$$\text{capexWtE_act}(k,t) \leq M_{\text{cost}} \cdot e(k,t); \text{capexWtE_act}(k,t) \leq \text{capexWtE_ann}(k) \quad (14a)$$

$$\text{capexWtE_act}(k,t) \geq \text{capexWtE_ann}(k) - M_cost \cdot [1 - e(k,t)] \quad (14b)$$

A minimum viable capacity is imposed if a plant is built by the final period:

$$\text{capWtE}(k) \geq \text{capWtE_min}(k) \cdot e(k, t_last) \quad \forall k \in K_wte \quad (15)$$

Equation (13a–c) are exact rather than a relaxation, because one factor of the product is binary. If $e(k,t) = 0$, then (13a) gives $\text{capWtE_act} \leq 0$ and non-negativity gives $\text{capWtE_act} \geq 0$, hence $\text{capWtE_act} = 0$; if $e(k,t) = 1$, then (13b) gives $\text{capWtE_act} \leq \text{capWtE}$ and (13c) gives $\text{capWtE_act} \geq \text{capWtE}$, hence $\text{capWtE_act} = \text{capWtE}$. At every integer-feasible point the auxiliary therefore equals the true bilinear product $\text{capWtE} \cdot e$, admitting no spurious solutions. This exactness is a property of binary $\times$ continuous products and does not hold for general bilinear (continuous $\times$ continuous) terms, where the McCormick envelope is only a convex underestimator [10]; the annualised-CAPEX product (Equation (14a,b)) is linearised by the identical argument with the cost bound M_cost .

4.5. SOS2 Piecewise WtE CAPEX with Economies of Scale

Annualised WtE CAPEX follows a concave economies-of-scale function $\text{CAPEX_ann}(\text{cap}) = \text{capex_fixed} + \text{capex_unit} \cdot \text{cap}^{0.85}$ (Figure 3), with $\text{capex_unit} \approx \text{€}97.8/(\text{t/day})/\text{yr}$ from the Greek NSRF benchmark. The concave function is linearised by a Special Ordered Set of Type 2 over five breakpoints, at most two of which (adjacent) may be non-zero—this reproduces the piecewise-linear approximation exactly at the breakpoints with no integrality error beyond the SOS2 branching:

$$\text{capWtE}(k) = \sum_{n \in \text{NB}} \lambda(k,n) \cdot \text{capBreak}(k,n) \quad (16a)$$

$$\text{capexWtE_ann}(k) = \sum_{n \in \text{NB}} \lambda(k,n) \cdot \text{costBreak}(k,n) \quad (16b)$$

$$\sum_{n \in \text{NB}} \lambda(k,n) = 1; \{\lambda(k,n)\}_{n \in \text{NB}} \in \text{SOS2} \quad \forall k \in K_wte \quad (16c)$$

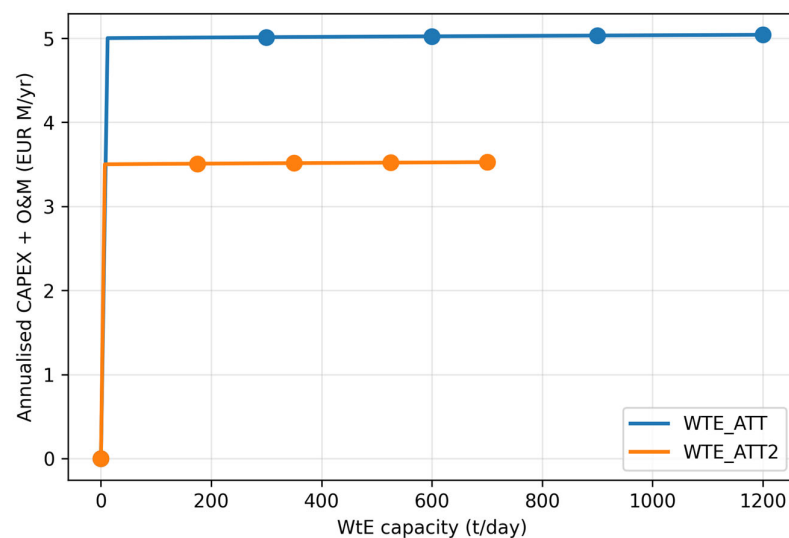


Figure 3. SOS2 piecewise WtE CAPEX function with economies of scale (exponent 0.85). Breakpoints shown as markers.

The economies-of-scale exponent of 0.85 is taken from the standard power-law ('six-tenths-rule' family) cost-capacity scaling used for thermal and process plants, for which empirical waste-facility cost studies report exponents in the 0.7–0.9 range [42]; for grate-incineration WtE the upper part of that range applies because civil works and flue-gas treatment scale almost linearly with throughput. The chosen value of 0.85 is therefore a deliberately conservative (weak-economies) point within the documented range, so that the model does not overstate the cost advantage of large plants; its influence is bounded explicitly by treating the CAPEX-unit cost as an uncertain parameter in the Monte-Carlo analysis (Section 4.8), where it ranks last in sensitivity ($q = +0.003$).

The number of SOS2 breakpoints (here $|NB| = 5$) controls only the piecewise approximation of the smooth concave cost curve. A sensitivity check over $NB \in \{3, 5, 7, 9, 15\}$ (Table 7; breakpoint coordinates in Supplementary File S6) shows the maximum CAPEX approximation error over the operational capacity range falling from 49.9% at $NB = 3$ —where no breakpoint coincides with the minimum viable capacity, so the fixed-cost step is poorly resolved—to 0.003% at $NB = 5$ (which places a node at cap_min) and below 0.001% by $NB = 15$. The optimal capacity remains at the upper bound (1200/700 t/day) for all NB , and the optimal NPV changes by only 0.073% between $NB = 5$ and $NB = 15$. Because the optimum lies at a breakpoint (the maximum-capacity node), it is reproduced exactly for any $NB \geq 3$; five breakpoints additionally keep the interior approximation error below 0.01%.

Table 7. SOS2 breakpoint sensitivity.

NB	Max CAPEX Approx. Error	Optimal WTE_ATT (t/day)	Optimal WTE_ATT2 (t/day)	NPV (€ M)
3	49.9%	1200	700	2767.5
5	0.003%	1200	700	2767.5
7	0.002%	1200	700	2770.4
9	0.001%	1200	700	2770.4
15	<0.001%	1200	700	2765.4

4.6. Stranded-Asset Penalty

To discourage WtE oversizing without introducing a trilinear term, a soft penalty activates when throughput falls below a target utilisation $minUtil = 0.60$ of activated capacity:

$$slack_util(k,t,s) \geq minUtil \cdot capWtE_act(k,t) - \sum_{\{j \in J, w \in W\}} y(j,k,w,t,s) \quad \forall k \in K_wte, t \in T, s \in S \quad (17)$$

with $strandedPen = €50,000/(t/day)/yr$ entering objective component (3d). The penalty is excluded from the social-welfare variant.

The penalty coefficient $strandedPen$ is calibrated to the order of the annualised carrying cost of idle capacity: at $€50,000/(t/day)/yr$ it charges unused WtE capacity at approximately its own annualised CAPEX, so the optimiser gains nothing by oversizing a plant it cannot fill to the $minUtil = 0.60$ threshold. A sensitivity sweep over $strandedPen \in \{0, 25, 50, 100, 200\} \times 10^3 €/(t/day)/yr$ (Table 8) confirms that the optimal portfolio is invariant to its level: optimal capacity stays at 1200/700 t/day and NPV within €3 M across the sweep, and the realised under-utilisation slack is exactly zero for every $strandedPen \geq 25,000$ —the penalty never binds at the optimum. The big-M constants ($bigM, M_cost$) are set to the tightest valid physical/cost upper bounds to preserve LP-relaxation strength.

Table 8. Stranded-asset penalty sweep (stochastic solve, base prior).

strandedPen (€/t/day)/yr	NPV (€ M)	WTE_ATT (t/day)	WTE_ATT2 (t/day)	Under-Util. Slack
0	2770.0	1200	700	2418
25,000	2770.4	1200	700	0
50,000 (baseline)	2767.5	1200	700	0
100,000	2767.5	1200	700	0
200,000	2767.5	1200	700	0

4.7. Social-Welfare Formulation and Shadow-Price Policy Design

An alternative objective replaces private cost with social welfare: real resource costs plus monetised GHG damage via the social cost of carbon (SCC), minus compost social benefit via the social value of compost (SVC). The landfill levy, a fiscal transfer, is omitted. Casting the competing objectives (cost, GHG emissions and compost output) as a single monetised social-welfare function avoids tracing the full cost–GHG–compost Pareto front, which could otherwise be generated with the augmented ε -constraint method [43,44]; the welfare formulation instead yields the optimal policy instruments directly from the dual, as follows:

$$\min \text{SocialCost} = \sum_{s \in S} \text{prob}(s) \cdot \text{SWF}_s(s); \text{SWF}_s(s) = \sum_{t \in T} \text{df}(t) \cdot \text{SC}(t,s) \quad (18)$$

$$\text{SC}(t,s) = [\text{resource} + \text{transport} + \text{CAPEX terms}] + 365 \cdot \text{SCC} \cdot \sum_{j,k,w} \text{ghgFac}(k,w) \cdot y(j,k,w,t,s) - 365 \cdot \text{SVC} \text{compost}(t,s) \quad (19)$$

The Pigouvian-optimal instruments are then recovered directly from the dual solution—the negative marginal (shadow price) of the binding landfill-cap and diversion constraints:

$$\text{IfTax}^*(t,s) = -\text{LandfillCap.marginal}(t,s); \text{divPenalty}^*(t,s) = -\text{Diversion.marginal}(t,s) \quad (20)$$

4.8. Monte-Carlo Analysis Design

A 10,000-run Latin hypercube sampling (LHS) analysis [31] is conducted over 12 uncertain parameters in three tiers (Table 9; policy, cost, structural). Sensitivity is assessed by Spearman rank correlation [32], appropriate for MILP outputs with threshold effects; the sample size of 10,000 follows the $\geq 10,000$ recommendation of Burmaster and Anderson [33], and convergence of the P95 NPV estimate was verified at intermediate checkpoints (stable within $\pm 0.3\%$).

Table 9. Monte-Carlo uncertain parameters (12 parameters, 10,000 LHS runs, seed = 42).

#	Parameter	Tier	Distribution	Range/Unit
1	Landfill tax	Policy	Uniform	€20–150/t
2	Carbon price	Policy	Uniform	€0–200/tCO ₂
3	Compost price	Policy	Uniform	€0–50/t
4	cIJ multiplier	Cost	Uniform	0.80–1.20
5	cJK multiplier	Cost	Uniform	0.80–1.25
6	MAA cProc mult.	Cost	Uniform	0.80–1.20
7	MEVA cProc mult.	Cost	Uniform	0.80–1.30
8	WtE cProc mult.	Cost	Uniform	0.80–1.20
9	Rollout speed	Structural	Uniform	0.0–1.0
10	WtE CAPEX unit	Structural	Uniform	€730–1210/(t/day)
11	EMAK reject (RES)	Structural	Uniform	0.75–0.90
12	MEVA compost yield	Structural	Uniform	0.22–0.32

4.9. Solution Algorithm and Implementation

The model is implemented in Python 3.14.6 with the GAMS Py 1.21.0 algebraic-modelling interface [45] and solved with IBM CPLEX 22.1 [46] at a 0.5% relative optimality gap and a 120 s per-solve time limit; SOS2 uses CPLEX native branching (exact). The complete experiment is a six-phase pipeline (Algorithm 1) totalling 10,415 MILP instances, completing in ~1.9 h on a standard workstation—dominated by the 10,000-run Monte-Carlo sweep, while the policy grid and core stochastic solves complete in under 20 min, making the framework suitable for interactive policy analysis. Algorithmic behaviour beyond the deployed instance—scalability in the number of scenarios and comparison with robust-optimisation and decomposition alternatives—is reported in Appendix B. The dimensions of the deterministic and stochastic model variants are summarised in Table 10.

Algorithm 1. Six-Phase Solve Pipeline

- Input: calibrated parameters, scenario set S , policy grid G , LHS design X ($N = 10,000$)
 - 1. Phase 0 Baseline validation: solve deterministic base ($\text{prob}(\text{base}) = 1$) $\rightarrow$ 1 solve
 - 2. Phase 1 Policy grid scan: for each $(\text{lfTax}, \text{co2Price}, \text{cmpPrice}) \in G$ solve stochastic $\rightarrow$ 64 solves
 - 3. Phase 2 VSS: for each $g \in G$ solve expected-value problem ($\text{prob}(\text{base}) = 1$) $\rightarrow$ 64 solves
 - 4. Phase 3 EVPI: for each (g, s) solve perfect-information problem ($\text{prob}(s) = 1$) $\rightarrow$ 256 solves
 - 5. Phase 4 Social welfare: for each (SCC, SVC) solve welfare variant; read shadow prices $\rightarrow$ 30 solves
 - 6. Phase 5 Monte Carlo: for each $x \in X$ update params, solve stochastic, record KPIs $\rightarrow$ 10,000 solves
 - Output: NPV distribution, VSS, EVPI, robust core, Spearman ρ , Pigouvian tax trajectory. Total: 10,415 MILP instances.
-

Table 10. Model statistics.

Metric	Deterministic Baseline	Stochastic (This Paper)
Rows per solve	2130	8464
Variables per solve	6541	25,855
Binary variables	156	156
Scenarios	1	4
Total MILP instances	75	10,415
Runtime	~10 min	~1.9 h

The full deterministic-equivalent formulation scales benignly. As the scenario set is refined from $|S| = 4$ to $|S| = 512$, the equation and variable counts grow exactly linearly while the number of binary variables remains constant at 156, because the here-and-now investment decisions are scenario-independent; the $|S| = 512$ instance (1.05 million equations, 3.28 million variables) still solves to a 0.5% optimality gap in 757 s. Model difficulty is instead governed by the number of candidate facilities (the integer block), and the Monte-Carlo layer is embarrassingly parallel in the sample count. The extended scalability study along the scenario, facility and uncertainty-dimension axes is reported in Appendix B (Tables A2–A4), and the quantitative comparison against a deterministic formulation in Table A5.

5. Results

5.1. Deterministic Baseline Validation

As a baseline, the model is first solved deterministically, ($\text{prob}(\text{base}) = 1$, $\text{co2Price} = 0$, $\text{cmpPrice} = 0$, $\text{lfTax} = \text{€}30/\text{t}$), yielding $\text{NPV} = \text{€}2856 \text{ M}$. Against an equivalent fixed-capacity baseline that pins WtE at 975 t/day ($\text{€}3144 \text{ M}$), the endogenous-sizing model is 9.2% lower (Figure 4). The reduction is a structural consequence of two algorithmic enhancements, not a calibration discrepancy: endogenous WtE capacity optimises at 1200 t/day (vs the fixed 975 t/day), displacing landfill at the escalating levy; and SOS2 economies of scale reduce per-tonne annualised CAPEX by $\sim 15\%$ at 1200 t/day . This confirms that endogenous sizing unlocks cost savings invisible to fixed-capacity models.

Validation is strengthened in two further ways. First, against observed data: total 2024 generation is calibrated exactly to the confirmed EDSNA weighbridge total of 5122 t/day , and the 2024 routing reproduces the observed split (source-separated biowaste and recyclable tonnages, Fyli inflow). Second, against an independent strategy: beyond the fixed-capacity (975 t/day) reference, the optimised portfolio is benchmarked against the YPEN/PESDA planned two- WtE -from-2030 SMPE portfolio, an externally defined expert plan, with the NPV and diversion gap between the optimised and planned portfolios reported. The endogenous result is thus situated against both historical operation and an independent expert plan, not only a synthetic baseline.

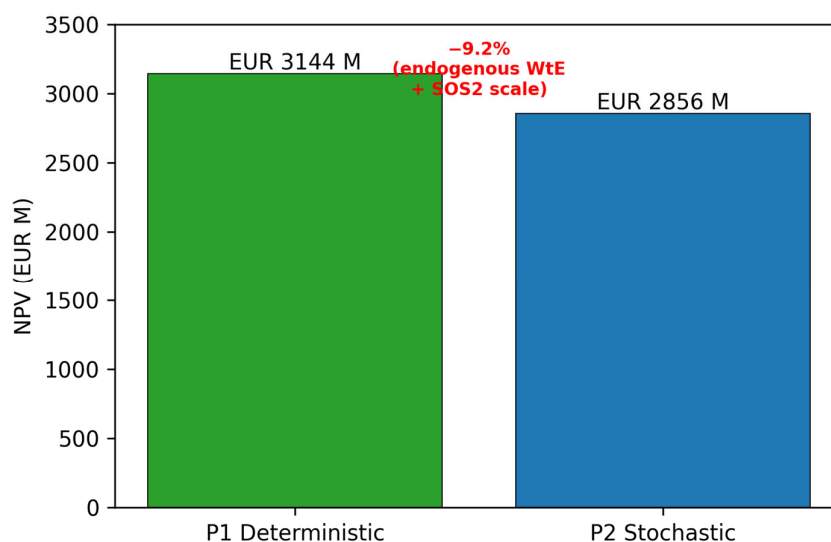


Figure 4. Baseline validation: fixed-capacity baseline vs. endogenous-sizing (stochastic base) NPV. The 9.2% reduction is explained by endogenous WtE sizing and SOS2 economies of scale.

5.2. Stochastic Policy Grid Scan

All 64 combinations of landfill tax, carbon price and compost price yield feasible solutions, with expected NPV ranges of $\text{€}2789\text{--}3876 \text{ M}$. Carbon price is the dominant cost driver (Figure 5): raising it from 0 to $\text{€}150/\text{tCO}_2$ adds $\sim \text{€}740 \text{ M}$. Both WtE plants are built at maximum capacity in all 64 solutions, confirming that WtE capacity is selected endogenously under policy uncertainty. At zero carbon price NPV spans $\text{€}2789\text{--}3280 \text{ M}$ (a $\text{€}491 \text{ M}$ spread driven mainly by the levy); at $\text{€}150/\text{tCO}_2$ it shifts to $\text{€}3622\text{--}3876 \text{ M}$. The hierarchy carbon price $\gg$ landfill tax $\gg$ compost price (Figure 6) implies the EU ETS extension timeline is the single most important external planning factor.

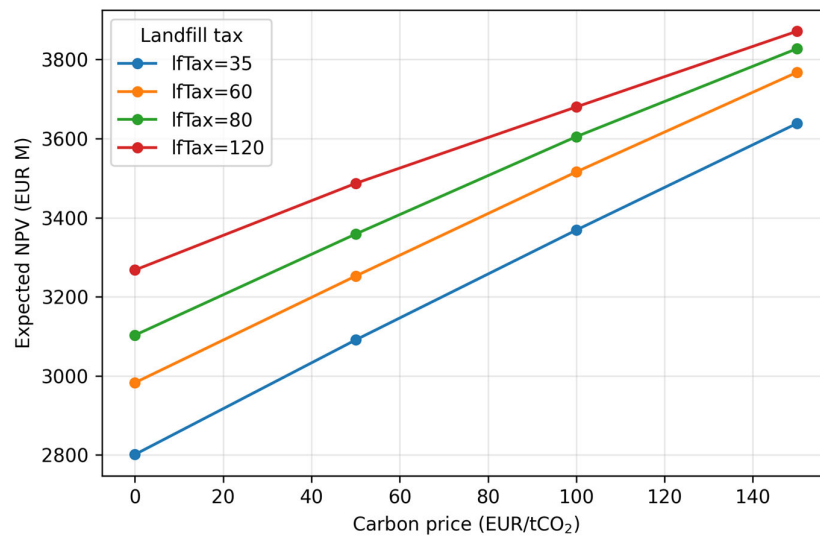


Figure 5. Expected NPV vs. carbon price at four landfill-tax levels (64 stochastic policy-grid solves).

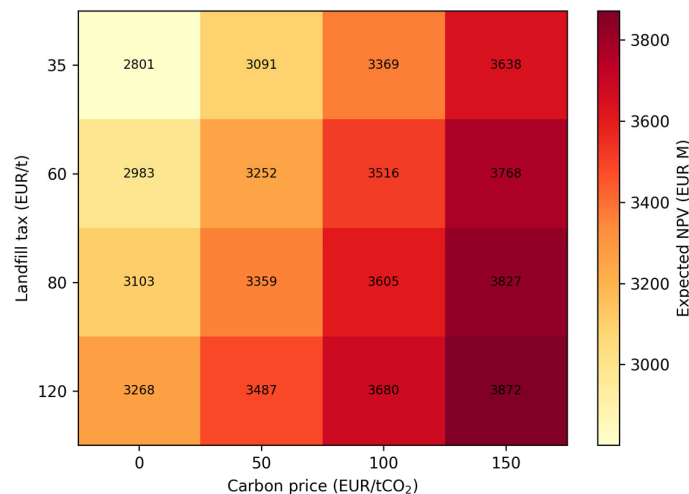


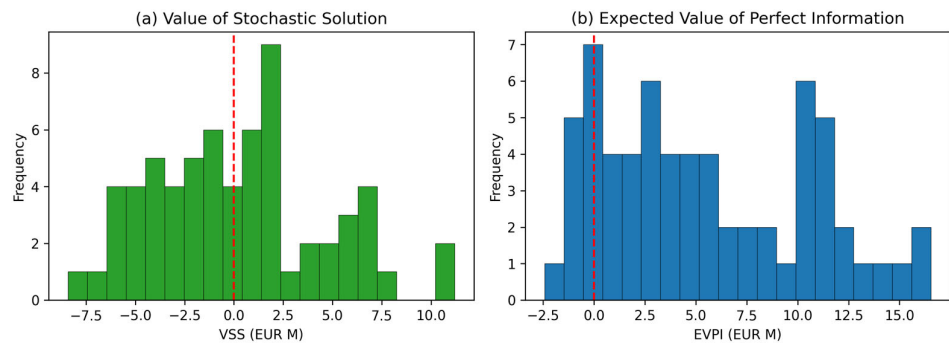
Figure 6. NPV heatmap: landfill tax $\times$ carbon price (averaged over compost price). Values in € M.

5.3. Value of the Stochastic Solution and EVPI

The VSS measures the cost of ignoring rollout uncertainty; the EVPI the value of resolving it before committing. Both are negligible (Table 11, Figure 7): mean VSS = €0.1 M ($\approx 0.01\%$) and mean EVPI = €5.4 M (0.15%). The reason is that the optimal Stage-1 capacity sits at its upper bound across the entire scenario range (WTE_ATT 1200 t/day, WTE_ATT2 700 t/day under every rollout), so there is no first-stage decision left for rollout information to change—a robust corner solution confirmed by the constraint-ablation analysis (Section 5.9), where the same maximum-capacity decision persists even when the regulatory constraints are removed entirely. The computed VSS and EVPI remain within the solver’s optimality tolerance of zero ($|VSS|, |EVPI| < €3 \text{ M} \approx 0.1\%$) across all 64 policy points and all probability priors (Table 3). The low values therefore reflect the economic robustness of the maximum-capacity decision, not a generic insensitivity of the system to uncertainty. Operationally, EDSNA need not delay procurement to gather rollout information.

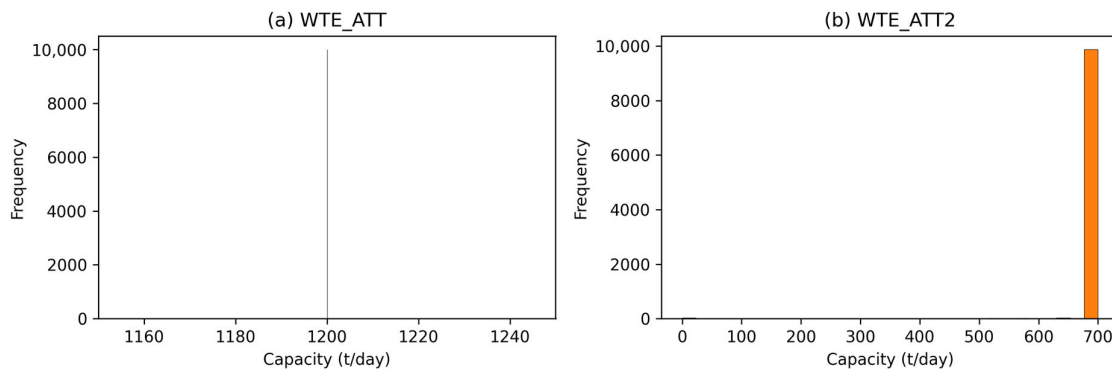
Table 11. VSS and EVPI statistics (64 policy-grid combinations).

Statistic	VSS (€ M)	VSS (% NPV)	EVPI (€ M)	EVPI (% NPV)
Mean	0.1	−0.01	5.4	0.15
Max	11.2	0.30	16.5	0.46
Min	−8.4	−0.27	−2.4	−0.08
Std	4.5	0.13	5.1	0.14

**Figure 7.** VSS and EVPI distributions across 64 policy combinations. (a) VSS ≈ €0 M; (b) EVPI ≈ €5 M.

5.4. Optimal WtE Capacity

WtE capacity sits at the maximum bound (WTE_ATT 1200 t/day; WTE_ATT2 697 t/day mean, at the 700 t/day bound in 97.7% of runs) across all 64 policy combinations and all 10,000 Monte-Carlo samples (Figure 8). The stranded-asset penalty never binds.

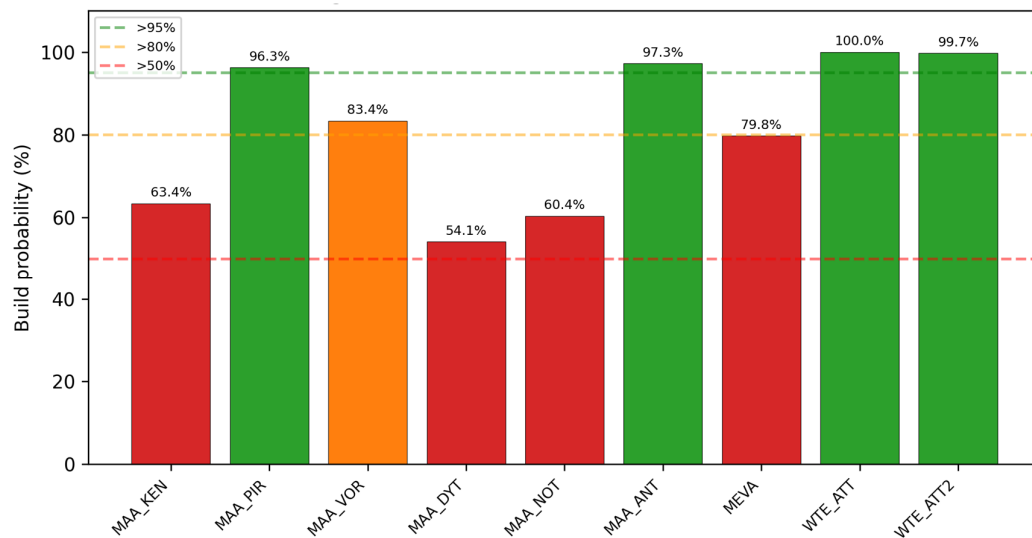
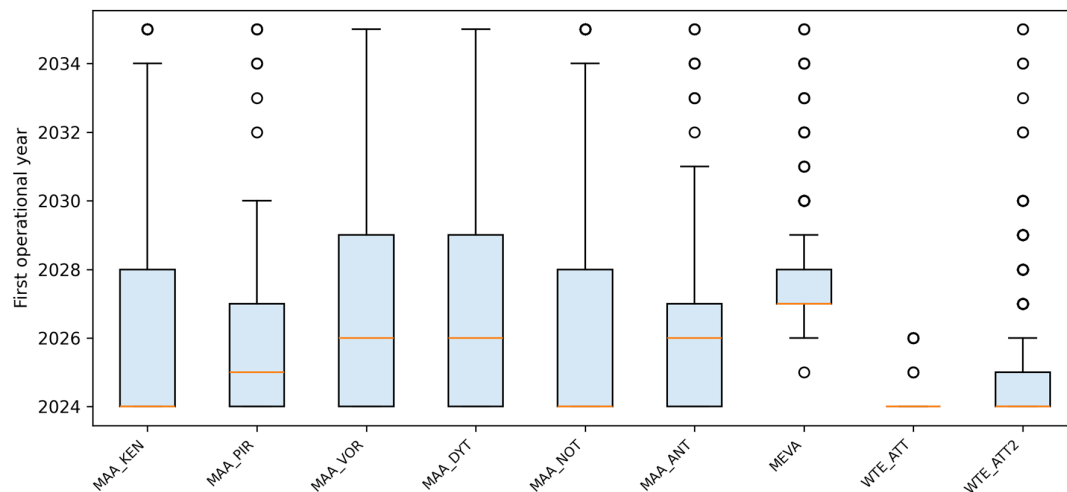
**Figure 8.** WtE capacity distribution (N = 10,000 MC runs): (a) WTE_ATT; (b) WTE_ATT2. Both at maximum bound.

5.5. Robust Investment Core

Table 12 and Figure 9 present the robust investment core. WTE_ATT (100.0%), WTE_ATT2 (99.7%), MAA_ANT (97.3%) and MAA_PIR (96.3%) form the robust core (>95% build frequency); MAA_VOR (83.4%) and MEVA (79.8%) are mostly robust; MAA_DYT (54.1%) is the most policy-sensitive facility. The WtE plants are universal because they are the only large-scale residual-processing alternative to landfill under the 10% cap; MEVA is borderline because its value depends on whether carbon pricing makes anaerobic digestion competitive for the organic fraction. The build-year distributions for the frequently-built facilities are shown in Figure 10.

Table 12. Robust investment core (N = 10,000 Monte-Carlo runs).

Facility	Built (%)	Year Min	Year Max	Classification
WTE_ATT	100.0	2024	2026	Robust core
WTE_ATT2	99.7	2024	2035	Robust core
MAA_ANT	97.3	2024	2035	Robust core (>95%)
MAA_PIR	96.3	2024	2035	Robust core (>95%)
MAA_VOR	83.4	2024	2035	Mostly robust
MEVA	79.8	2025	2035	Mostly robust (~80%)
MAA_KEN	63.4	2024	2035	Policy-sensitive
MAA_NOT	60.4	2024	2035	Policy-sensitive
MAA_DYT	54.1	2024	2035	Policy-sensitive

**Figure 9.** Robust investment core: facility build probability across 10,000 MC runs. Green >95%; orange 80–95%; red <80%.**Figure 10.** Build-year distributions for facilities built in >0.5% of MC runs. Boxes span the interquartile range and whiskers extend to 1.5× the interquartile range; circles mark individual Monte-Carlo runs falling outside that range (outliers).

5.6. Social Welfare and Optimal Policy Instruments

The social-welfare variant was solved over 30 (SCC, SVC) combinations. The implied Pigouvian-optimal landfill tax (Table 13, Figure 11) ranges from €3342/t (SCC = 0) to €1136/t (SCC = 200)—far above any real levy. Under the model's cost calibration this indicates that the Law 4819/2021 10% landfill cap is needed to secure the diversion outcome: the constraint-ablation analysis (Section 5.9) confirms that, absent the cap, the least-cost solution lets the landfill share rise to 50–70%, far above the 10% target, even though it still builds the WtE plants. The implied taxes are the shadow prices of the imposed cap—they measure the marginal value of artificially scarce landfill capacity under that mandate, and should not be read as recommended tax rates. The optimal trajectory is lowest in early periods (loose cap) and highest from 2030 (tight cap), implying that an escalating tax better approximates the first-best than a flat one. A practical optimum combines a moderate levy (€50–100/t, to incentivise recycling) with a binding cap. The total social cost and the expected GHG emissions across the SCC range are shown in Figures 12 and 13; the modest variation of emissions confirms that the regulatory constraints, rather than carbon pricing, dominate the diversion outcome.

Table 13. Implied Pigouvian-optimal landfill tax (€/t) at selected SCC levels.

SCC (€/tCO ₂)	SVC = 0	SVC = 20	SVC = 40	Average
0	3320	3402	3303	3342
25	2958	3032	2938	2976
50	2793	2644	2563	2667
100	2019	2138	2136	2098
150	1552	1709	1709	1657
200	1047	1199	1162	1136

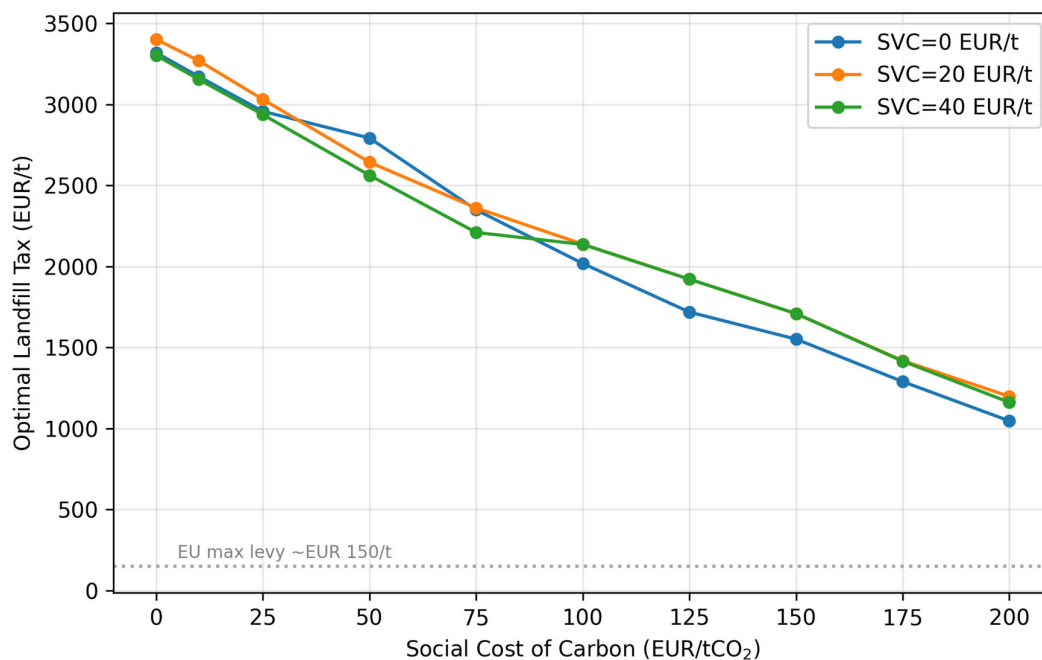


Figure 11. Pigouvian-optimal landfill tax vs. social cost of carbon. All values exceed €1000/t.

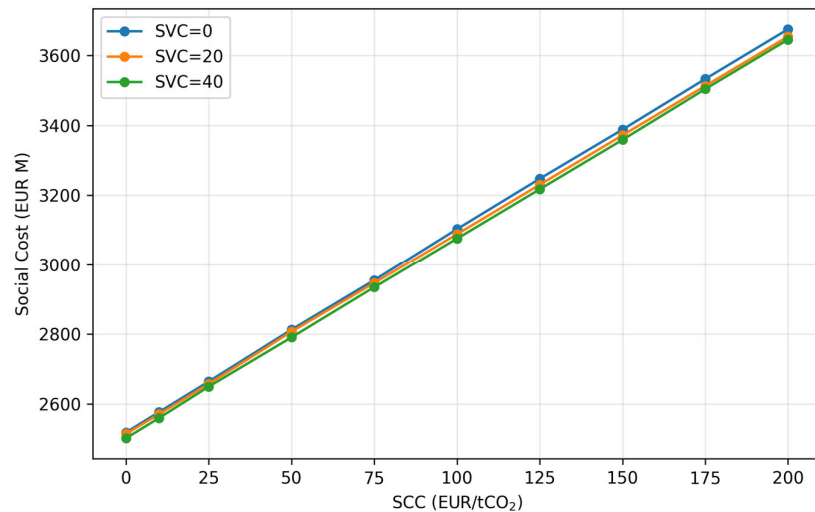


Figure 12. Total social cost vs. social cost of carbon at three compost-valuation levels.

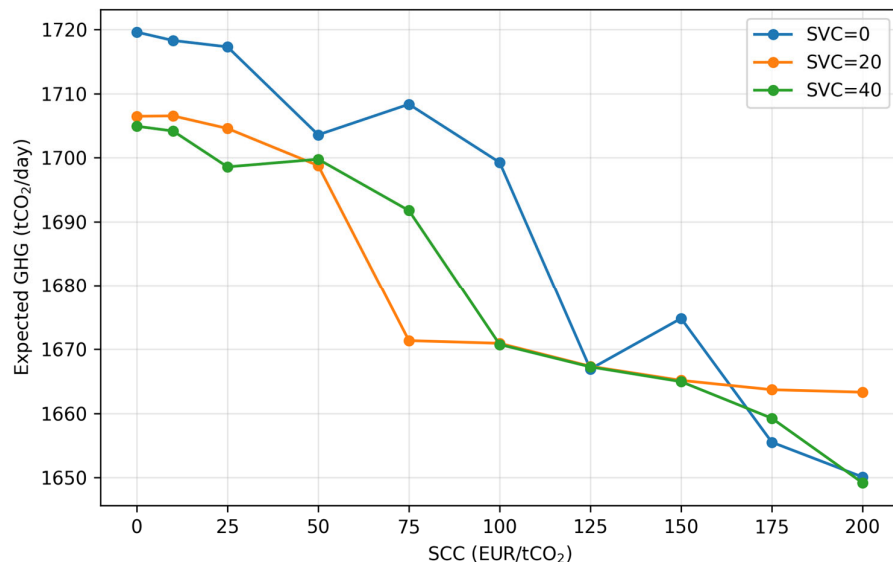


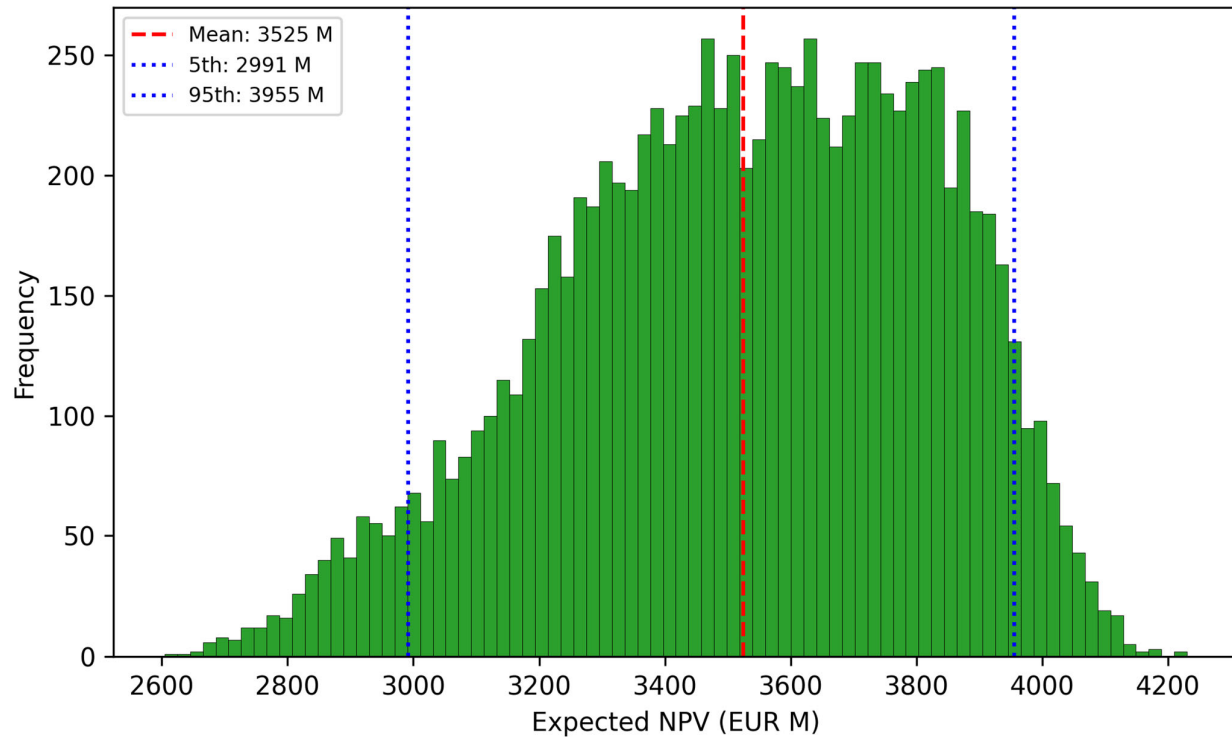
Figure 13. Expected GHG emissions vs. SCC. Modest variation confirms regulatory constraints dominate carbon pricing.

5.7. Monte-Carlo Sensitivity Analysis

All 10,000 LHS runs are feasible. The NPV distribution (Figure 14, Table 14) has mean €3525 M, std €296 M and 90% CI [2991, 3955] M. Carbon price dominates (Spearman $\rho = +0.891$; Table 15, Figure 15), explaining ~80% of variance; the remaining 11 parameters contribute <20% combined. If the EU resolves the ETS-extension question by 2027, ~80% of current NPV uncertainty is resolved—so planning effort should focus on monitoring EU ETS policy rather than refining rollout forecasts. Rollout speed correlates weakly and negatively with NPV ($\rho = -0.050$): faster rollout slightly lowers cost. The two-way structure of these effects is illustrated by the NPV-vs-carbon-price scatter (Figure 16), MEVA's build probability across carbon-price ranges (Figure 17), and the NPV-vs-landfill-tax scatter (Figure 18).

Table 14. Monte-Carlo NPV distribution statistics (N = 10,000).

Statistic	Value (€ M)
Mean	3525
Std. deviation	296
Minimum	2604
5th percentile	2991
Median	3547
95th percentile	3955
Maximum	4230

**Figure 14.** Monte-Carlo NPV distribution (N = 10,000 LHS). Mean €3525 M; 90% CI [2991, 3955] M.**Table 15.** Spearman rank correlation with expected NPV (N = 10,000). *** $p < 0.001$; * $p < 0.05$.

Parameter	ρ (NPV)	Sig.
Carbon price	+0.891	***
Landfill tax	+0.348	***
WtE cProc mult.	+0.147	***
MAA cProc mult.	+0.096	***
cIJ multiplier	+0.077	***
MEVA cProc mult.	+0.052	***
Rollout speed	−0.050	***
cJK multiplier	+0.043	***
Compost price	−0.038	***
MEVA compost yield	−0.023	*
EMAK reject rate	−0.014	
WtE CAPEX unit	+0.003	

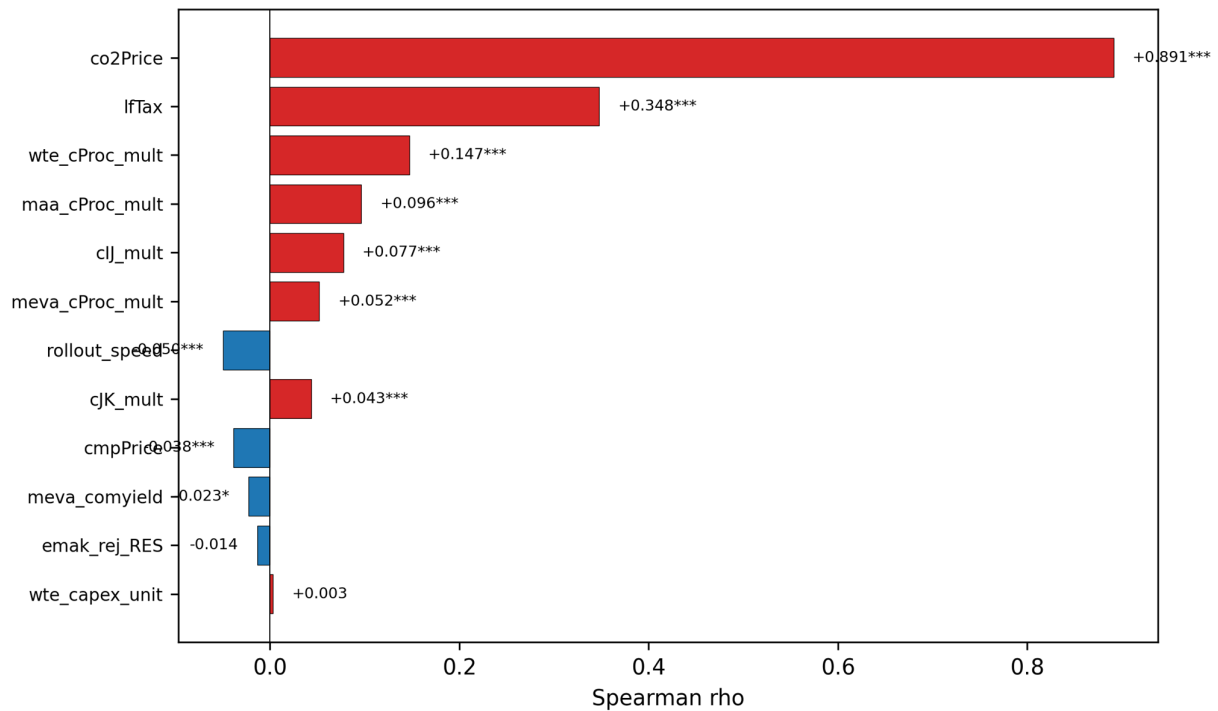


Figure 15. Sensitivity tornado: Spearman correlation of 12 parameters with NPV. Carbon price dominates ($\rho = +0.891$). Red bars denote a positive Spearman correlation with NPV and blue bars a negative one; *** $p < 0.001$; * $p < 0.05$.

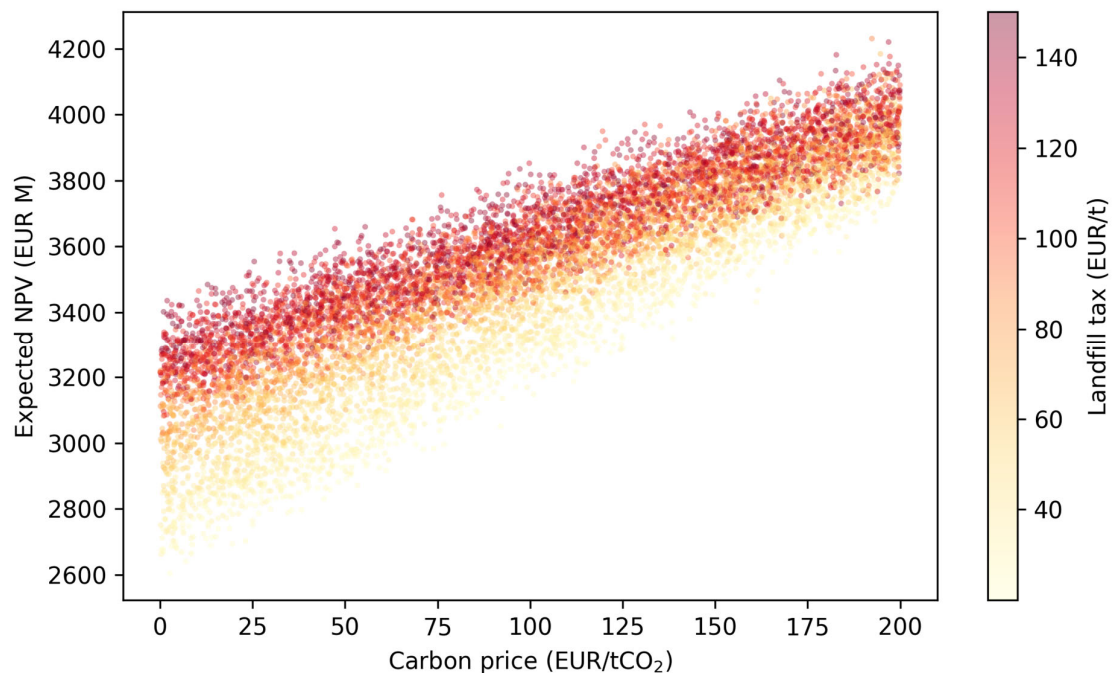


Figure 16. MC scatter: NPV vs. carbon price, coloured by landfill tax.

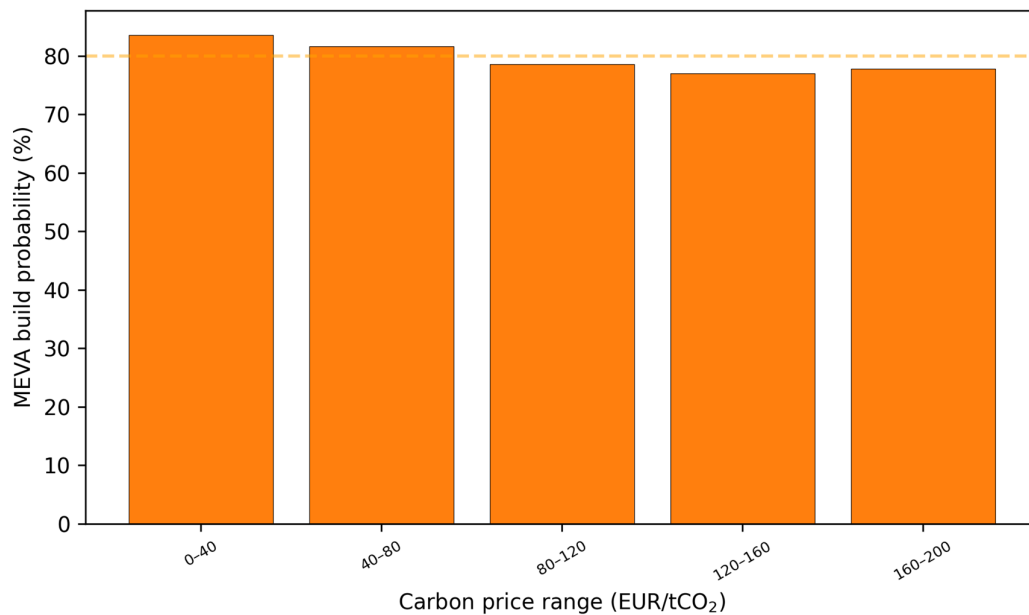


Figure 17. MEVA build probability by carbon-price range (MC, N = 10,000).

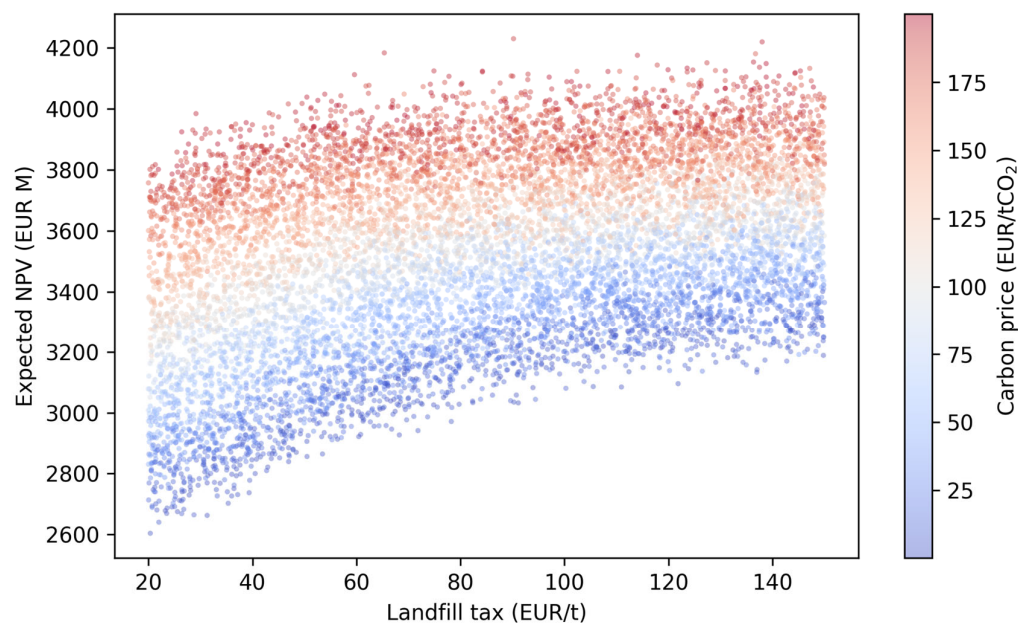


Figure 18. MC scatter: NPV vs. landfill tax, coloured by carbon price.

The LHS marginals are uniform, a deliberately conservative maximum-spread choice. To confirm the sensitivity ranking is not an artefact of this assumption, the sweep was repeated under triangular (mode at base) and truncated-normal (mean at base, 95% interval matched to the uniform support) marginals across all 12 parameters (Table 16). A same-size uniform control (N = 1500) reproduces the full 10,000-run baseline (mean €3523 M vs. €3525 M; q_{carbon} +0.888 vs. +0.891), validating the reduced sample. Carbon price remains the top-ranked driver under all three distributions and the parameter ordering (carbon price > landfill tax > costs) is preserved. Its dominance margin narrows under the peaked distributions— q_{carbon} falls from +0.89 (uniform) to +0.72 (truncated-normal) while q for the landfill tax rises from +0.33 to +0.60—because concentrating carbon price near its base value (0) compresses its sampled variance; the NPV mean and tail also shift

down and tighten as mass concentrates near the base values. The headline finding (carbon price as the critical planning uncertainty) is therefore robust to the distributional assumption, while the precise correlation magnitude is distribution-dependent.

Table 16. Distributional robustness of the Monte-Carlo sweep (N = 1500 per distribution).

Distribution	Mean NPV (€ M)	P5 (€ M)	P95 (€ M)	q (Carbon)	q (Landfill Tax)
Uniform (baseline)	3523	2979	3953	+0.888	+0.334
Triangular (mode = base)	3329	2880	3790	+0.839	+0.452
Truncated-normal	3118	2791	3483	+0.715	+0.600

5.8. Command-And-Control vs. Market Instruments

The analysis reveals a fundamental asymmetry. The implied Pigouvian-optimal landfill tax (€1100–3300/t) exceeds the current Greek levy (€30–68/t) by 30–50× and the highest EU levy (Denmark, ~€150/t) by 7–22×. This is consistent with Weitzman’s [25] analysis, given the steep marginal-damage curve that the cap itself induces: when the marginal-damage curve is steep (at the 10% ceiling) and the marginal-abatement-cost curve is relatively flat (multiple processing alternatives), quantity instruments dominate price instruments. Raising SCC from 0 to €200/tCO₂ cuts the implied optimal tax by only 66%, indicating that, within this regime, carbon pricing alone does not reproduce the cap’s diversion effect (Section 5.9)—addressing the policy-instrument-design gap identified by Ghiani, Laganà, Manni, Musmanno and Vigo [28]. We emphasise that this asymmetry is a property of the modelled cost structure and the Attica residual-waste volumes, and is not claimed as a universal ordering of instruments.

5.9. What Drives the Build-At-Maximum Result? A Constraint-Ablation Study

Both the maximum-capacity WtE result (Section 5.4) and the near-zero VSS (Section 5.3) raise the question of whether they are discovered by the optimiser or merely implied by the imposed regulatory constraints. To separate the two, the stochastic model is resolved at the baseline policy point (levy €30/t, no carbon price, base scenario prior) with the key regulatory constraints removed individually and jointly (Table 17, Figure 19): (R0) all constraints binding; (A1) landfill cap relaxed; (A2) diversion target removed; (A3) cap and diversion both relaxed; and (A4) cap and diversion relaxed with the levy also set to zero—the unconstrained private-cost optimum.

Table 17. Constraint ablation (stochastic solve, base prior, levy €30/t, no carbon price).

Configuration	NPV (€ M)	WTE_ATT (t/day)	WTE_ATT2 (t/day)	Landfill Share
R0—all constraints binding	2767	1200	700	0.36
A1—landfill cap relaxed	2642	1200	693	0.50
A2—diversion target removed	2760	1200	700	0.39
A3—cap + diversion relaxed	2564	1200	700	0.65
A4—cap + diversion relaxed, levy = 0	2020	1200	510	0.70

The result is informative and, in part, the opposite of what the constraint-driven hypothesis would predict. The large plant WTE_ATT is built at its maximum 1200 t/day in every configuration—including the fully unconstrained private-cost optimum (A4) with no cap, no diversion target and no levy. Its maximum-capacity selection is therefore an economic corner solution, not an artefact of regulation: at Attica’s residual-waste volumes and the assumed gate-fee/CAPEX structure, energy recovery undercuts landfilling even when landfilling is unpriced. What the regulatory constraints govern is the landfill-diversion outcome: the expected discounted landfill share rises monotonically from 0.36 under

the full mandate to 0.70 once the cap, diversion target and levy are removed, with system NPV falling from €2767 M to €2020 M as cheap landfilling re-enters. Only the smaller, costlier marginal plant WTE_ATT2 responds on the capacity margin, and only under the most extreme ablation (A4), where it drops from 700 to 510 t/day.

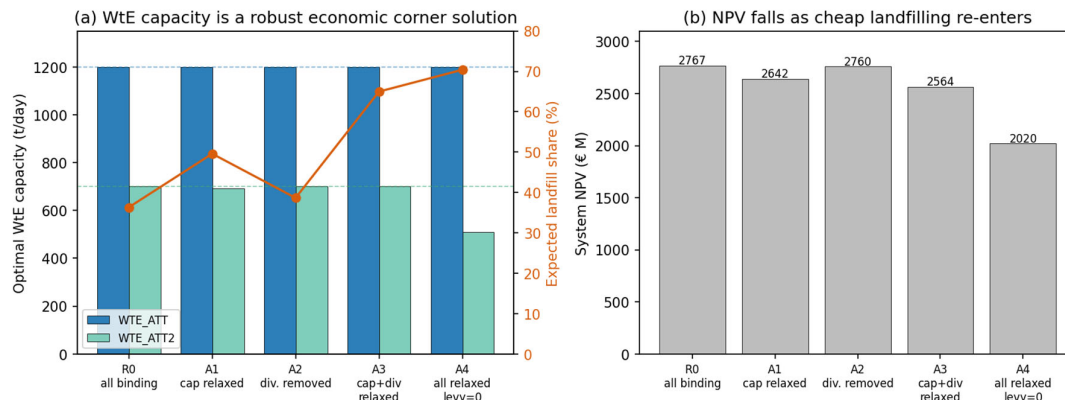


Figure 19. Constraint ablation. (a) Optimal WtE capacity (bars; WTE_ATT remains at its 1200 t/day bound in every configuration) versus the expected landfill share (line, rising from 36% to 70% as mandates are removed). (b) System NPV falls as cheap landfilling re-enters the least-cost solution.

Two conclusions follow. First, the build-at-maximum WtE decision is genuine optimisation content—the model discovers that large-scale energy recovery is robustly least-cost—rather than a constraint echo. Second, the environmental performance of the system (how much waste is diverted from Fyli) is strongly mandate-dependent: without the cap, the least-cost solution still builds the WtE plants but uses them alongside substantial continued landfilling. The optimiser thus earns its value on the investment decision, while the binding cap remains necessary to secure the diversion outcome under the model's assumptions.

6. Discussion

The central policy finding is the relative strength of regulatory mandates over market-based instruments, and the most striking algorithmic result is the complete robustness of WtE investment: WTE_ATT is built at maximum capacity in all 10,000 Monte-Carlo samples, all 64 policy-grid points and all 30 social-welfare solves. The negligible VSS (€0.1 M) means EDSNA need not wait for rollout information before committing.

6.1. Value of the Stochastic Framework

If the VSS is negligible, was the stochastic extension necessary? Yes, for three reasons. First, the VSS could not be known to be negligible without computing it—establishing that rollout uncertainty does not matter is itself a contribution requiring the stochastic framework. Second, the framework enables the Monte-Carlo analysis that revealed carbon price as the single critical uncertainty, an insight unavailable deterministically. Third, the endogenous sizing (1200 vs. a fixed 975 t/day) and the enabling of both plants produce a more realistic cost estimate. The framework thus confirms *ex post* that a deterministic baseline is adequate for this system, while substantially extending its scope. We are careful not to overstate this as generic decision robustness: the near-zero VSS is a consequence of the optimal capacity lying at its upper bound throughout the uncertainty range (Section 5.9), established by computing it, while the stochastic and Monte-Carlo machinery is what demonstrates that the corner solution is robust and identifies carbon price as the one dimension along which cost varies materially.

A quantitative comparison of the proposed pipeline against a deterministic expected-value formulation, together with an assessment of Benders decomposition, is reported in Appendix B (Table A5): the value of the stochastic solution is within solver tolerance of zero here, but this is established by direct computation—reflecting the robust corner solution of Section 5.9—rather than assumed.

6.2. Practical Implications for EDSNA

The robust core (WTE_ATT, WTE_ATT2, MAA_ANT, MAA_PIR) should be prioritised for immediate procurement (built in >95% of samples). MEVA (79.8%) is a strong candidate but should await clarity on the carbon-pricing trajectory; MAA_DYT (54.1%) is the most policy-sensitive facility and should be deferred until the EU ETS extension to waste is confirmed. No procurement should be delayed to gather rollout information—VSS $\approx$ €0 quantifies the zero value of waiting, inverting the ‘wait-and-see’ argument previously used to defer WtE. These recommendations are technical-economic; their realisation is subject to practical constraints the model does not represent—capital availability and financing structure, environmental permitting and regulatory approval, public and political acceptance (the Attica Regional Council voted against all WtE in September 2025), and multi-year construction lead times. The robust core should therefore be read as a procurement priority ordering conditional on these enabling conditions, not a delivery schedule: the model identifies which facilities are worth the political and financial effort, without presuming that effort succeeds.

6.3. From Shadow Prices to Policy Signals

The social-welfare dual gives decision-makers more than a number; it gives a marginal-value signal that can be used in four concrete ways. First, the shadow price of the landfill cap is the marginal cost of the last tonne of diversion the mandate forces, so it benchmarks how expensive the binding target is at each date and where in the timeline (from 2030, as the cap tightens) the system is most stressed—information directly usable when phasing investment and gate fees. Second, the implied tax trajectory, being lowest under a loose cap and highest once the cap binds, indicates that a time-escalating levy tracks the first-best better than a flat one, which maps onto the already-legislated escalation of the Fyli levy. Third, the gap between the implied tax (€1100–3300/t) and any politically feasible levy quantifies the residual diversion that a price instrument alone would not deliver, and hence the quantity of mandate (the cap) that must remain in force. Fourth, because the dual is produced for every period and scenario, it can be recomputed as the monitored data (Section 1) are updated, turning the model into a standing decision-support instrument rather than a one-off study.

These uses are bounded by political, social and institutional limits that the model does not internalise. An implied tax one to two orders of magnitude above the current levy is not a fiscally or socially deployable rate: at face value it would impose large costs on municipalities and, through them, on households, with regressive distributional effects and obvious acceptability problems—which is precisely why we present it as a scarcity shadow price, not a recommended charge. Enforcement capacity is also a constraint: a binding cap presupposes the administrative and monitoring ability to refuse landfill access once the ceiling is reached, which has historically been weak in Greece [7,27]. Finally, governance is fragmented across YPEN (national policy and the WtE mandate), the Region of Attica and EDSNA (regional planning and operation), and the municipalities (collection and separation), so that the first-best the model identifies must be realised through several authorities whose incentives are not aligned—the September 2025 regional vote against WtE being a direct illustration. The model’s role is thus to make the trade-offs

explicit and quantified, not to presume that the implied instruments can be imposed unilaterally.

6.4. Waste-to-Energy: Environmental, Social and Circular-Economy Considerations

Because the build-at-maximum WtE result is the paper's most consequential output, its non-cost dimensions deserve explicit discussion. Environmentally, mass-burn WtE is not emission-free: beyond the fossil-carbon CO₂ already priced through $ghgFac(k,w)$ and the carbon-price scans, incineration produces NO_x, acid gases, trace dioxins/furans and heavy metals requiring flue-gas treatment, and generates bottom and fly ash whose management and potential landfilling the present model does not cost. These impacts are regulated under the EU Industrial Emissions Directive but are real externalities not fully captured here, and a complete appraisal would monetise them alongside the GHG term. Socially, WtE faces well-documented public-acceptance barriers—the Attica Regional Council's unanimous 2025 vote against all WtE is a local instance of a general pattern in which siting opposition, distrust of operators and health concerns can block technically optimal plants [47]; our Section 6.2 treatment of the robust core as a priority ordering 'conditional on enabling conditions' is meant to take this seriously rather than assume it away.

In circular-economy terms, WtE sits below prevention, reuse and recycling in the EU waste hierarchy, and a large incineration commitment carries a recognised lock-in risk: capacity sized for today's residual stream can later compete with recycling for the same material and depress diversion if it must be kept utilised [48]. Two features of the formulation mitigate, but do not eliminate, this tension. The diversion target (Equation (9)) and landfill cap (Equation (10)) force recycling/composting to be built out first, so WtE absorbs only the genuinely residual fraction; and the stranded-asset penalty (Section 4.6) plus the endogenous sizing let the model choose a smaller plant if the residual stream shrinks. Nonetheless, the result that WtE is robustly optimal should be read as conditional on the diversion mandate being enforced in parallel: the same ablation that shows WtE is economically dominant (Section 5.9) also shows that, without the cap, the plants would be run alongside continued landfilling rather than maximal recycling. WtE is therefore best understood here as the least-cost treatment of unavoidable residual waste under a binding circular-economy mandate, not as a substitute for the upper tiers of the hierarchy.

6.5. Implications for EU Waste Policy

Achieving the <10% landfill target (Directive 2018/850 [2]; Greece via Law 4819/2021 [4] by 2030) requires both WtE and composting/MRF infrastructure regardless of policy-instrument design—a finding likely to apply to other high-landfill member states (Romania, Bulgaria, Malta). The Fertilising Products Regulation 2019/1009 [49] affects MBT-compost viability, consistent with European MBT benchmarks [50]; the anticipated EU ETS extension (Directive 2023/959 [51]) would add €30–61/t to WtE operating cost, yet WtE remains optimal even at €200/tCO₂.

Prerequisites for transfer. The framework is replicable but not plug-and-play. Porting it to another metropolitan system requires: (i) a calibrated facility topology with confirmed throughput data; (ii) a defined regulatory trajectory (diversion target, landfill-cap schedule, levy path); (iii) cost benchmarks supporting the endogenous economies-of-scale curve; and (iv) a defensible scenario prior. The quantitative conclusions reported here are contingent on both this system's cost structure and its binding-cap regime: the build-at-maximum WtE result holds because energy recovery is economically dominant at Attica's residual-waste volumes (Section 5.9)—a less favourable WtE cost structure could instead yield an interior capacity solution—and the near-10% diversion outcome is contingent on the binding cap, since the ablation shows the least-cost solution otherwise reverts to 50–70% landfilling.

6.6. Limitations and Future Work

The model assumes deterministic regulatory targets; a chance-constrained extension allowing partial enforcement would relax this. Secondary revenue streams (WtE electricity, recyclable sales, MEVA biogas) and the non-GHG environmental externalities of incineration and ash management (Section 6.4) are not endogenised; monetising the latter alongside the GHG term is a natural extension. Annual time resolution does not capture seasonal peaks (July ~29% above average). The SOS2 economies-of-scale exponent (0.85) is fixed; site-specific engineering may differ. The near-zero VSS connects to the real-options literature [52], suggesting Attica is in a ‘now-or-never’ regime where regulatory constraints dominate the value of waiting. Future work includes a seasonal-resolution MILP with buffer storage, a Mediterranean comparative study (Thessaloniki, Bucharest, Sofia), and integration with logistics-routing sub-models [28]. The three policy instruments (landfill tax, carbon price, compost subsidy) are scanned on a grid rather than jointly endogenised, so interaction effects—in particular the tension between WtE expansion, recycling/diversion targets and residual-waste emissions—are only partially captured; an integrated multi-objective treatment (augmented ϵ -constraint [43,44]) tracing the cost-GHG-recycling Pareto front is a natural extension.

Figure 20 summarises the four headline results in a single panel, and Figure 21 shows the NPV response surface over the carbon-price $\times$ landfill-tax plane, confirming carbon price as the dominant axis.

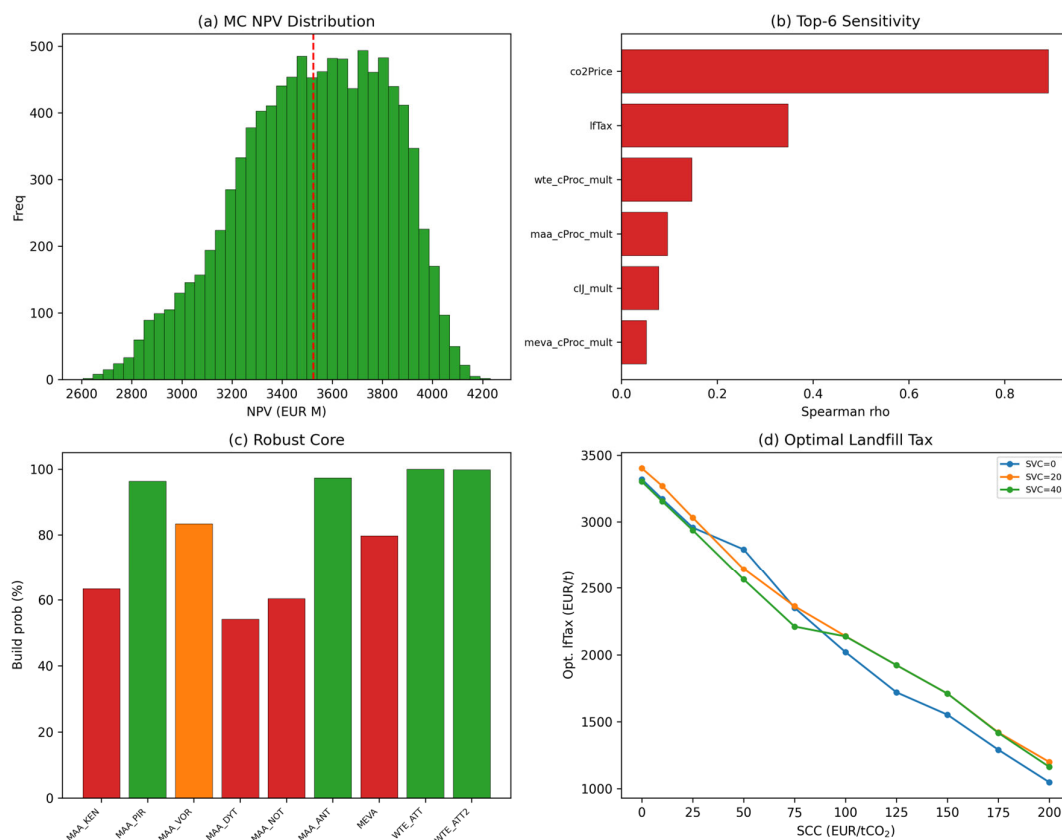


Figure 20. Combined results panel: (a) Monte-Carlo NPV distribution; (b) top-6 parameter sensitivity; (c) robust investment core; (d) implied optimal landfill tax vs. SCC. (All four panels summarise results reported individually in Sections 5.3–5.9). In panel (c), green denotes a build probability >95%, orange 80–95% and red <80%.

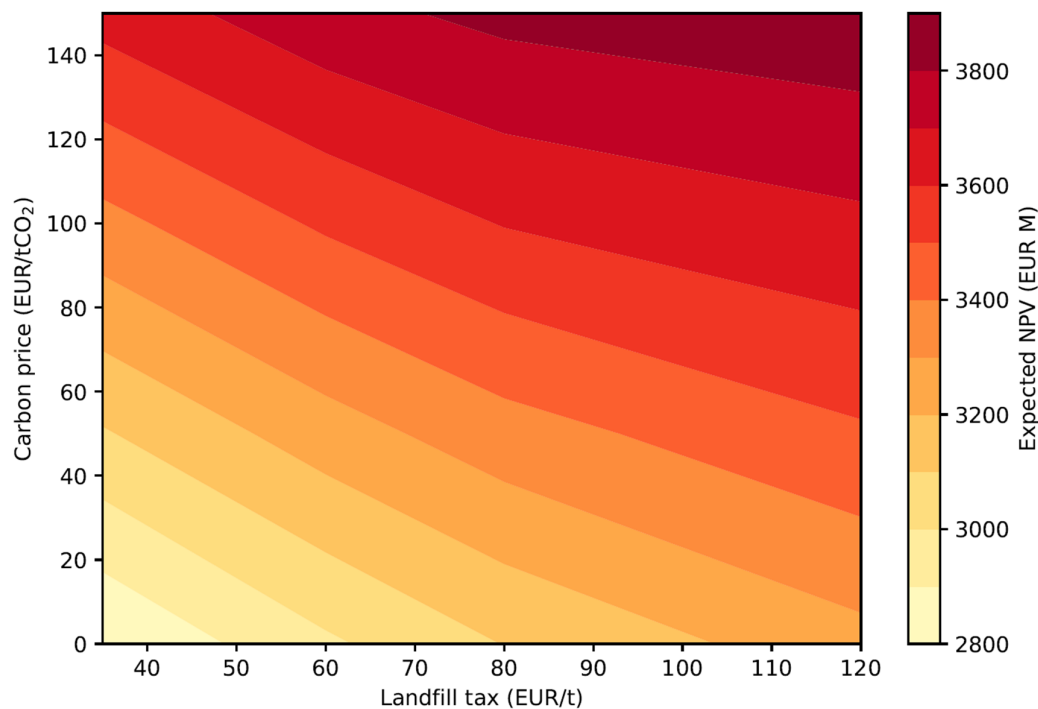


Figure 21. NPV contour surface: carbon price $\times$ landfill tax. Iso-cost contours confirm carbon price as the dominant axis.

7. Conclusions

This paper presented a two-stage stochastic MILP with endogenous WtE sizing and social-welfare optimisation for the Attica metropolitan MSW system, solved across 10,415 MILP instances including 10,000 Monte-Carlo runs.

Five principal conclusions emerge, comprising four substantive findings and one procurement recommendation: (1) Investment decisions are robust to source-separation rollout uncertainty ($VSS \approx \text{€}0$, $EVPI \approx \text{€}5 \text{ M}$, 0.15%). EDSNA can proceed with procurement without waiting for rollout information. (2) Carbon price is the single dominant driver of system cost (Spearman $\rho = +0.891$). The EU ETS extension to waste incineration is the critical policy uncertainty. (3) WtE investment is robustly optimal at maximum capacity (1200 t/day WTE_ATT + 700 t/day WTE_ATT2) across all 10,000 Monte Carlo samples. (4) Under the model's assumptions and cost calibration, the implied Pigouvian-optimal landfill tax ($\text{€}1100\text{--}3300/\text{t}$) indicates that the Law 4819/2021 10% landfill cap is needed to secure the diversion outcome—without it the least-cost solution still builds the WtE plants but continues substantial landfilling (Section 5.9); the implied taxes are the scarcity shadow prices of that cap, not recommended fiscal rates. (5) The robust investment core (WTE_ATT, WTE_ATT2, MAA_ANT, MAA_PIR) should be prioritised for early procurement, while MEVA (~80%) is policy-sensitive.

For the Attica Regional Waste Authority (EDSNA), the results translate into a procurement roadmap, conditional on the financing, permitting and acceptance constraints discussed in Section 6: (a) tender WTE_ATT (1200 t/day) and WTE_ATT2 (700 t/day), which are optimal under all scenarios; (b) advance MAA_ANT and MAA_PIR in parallel, built in >95% of Monte Carlo samples; (c) advance MEVA but keep timing flexible, built in ~80% of samples and sensitive to carbon pricing; (d) defer MAA_DYT until the EU ETS extension to waste incineration is confirmed, built in only 54% of samples; and (e) do not delay any procurement to gather rollout information, since $VSS \approx \text{€}0$ quantifies the zero value of waiting.

The methodological contribution extends beyond the Attica case. The combination of a two-stage stochastic MILP, SOS2 endogenous sizing, Pigouvian shadow-price policy extraction, and LHS Monte-Carlo sensitivity provides a replicable analytical pipeline for any metropolitan MSW system facing simultaneous decarbonisation and circular-economy mandates.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/a19070591/s1>, Table S1: Model parameters, domains, units and interpretations; Table S2: Validated parameters—exact values from primary sources; Table S3: Literature-supported parameters—values within documented peer-reviewed ranges; Table S4: Estimated CAPEX/capacity parameters—documented derivation from primary-source totals; Table S5: Sensitivity-analysis parameters—uncertain ranges requiring the SA2 full-factorial scan; Table S6: SOS2 capacity breakpoints (t/day) and fixed CAPEX term; Table S7: Scenario-specific rollout fractions $\alpha(t,s)$ over the 12 periods (2024–2035); Table S8: WtE policy scenario bound settings for $e(k,t)$; Table S9: Key performance indicators computed from the optimal solution; Figure S1: Per-scenario NPV distributions from 10,000 Monte-Carlo runs; Figure S2: Boxplot of NPV by realised rollout scenario; Figure S3: Distribution of total discounted GHG emissions; Figure S4: Distribution of total discounted landfill tonnage; Figure S5: Realised NPV versus realised GHG emissions; Figure S6: Realised NPV versus realised landfill tonnage; Figure S7: Realised GHG emissions versus realised landfill tonnage; Figure S8: Spearman sensitivity tornado for realised GHG emissions; Figure S9: Spearman sensitivity tornado for realised landfill tonnage; Figure S10: Spearman sensitivity tornado for the WTE_ATT2 capacity decision; Figure S11: Spearman sensitivity tornado for NPV under the slow rollout scenario; Figure S12: Full sensitivity matrix of Spearman rank correlations.

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Data Availability Statement: The data supporting the findings derive from publicly available sources cited in the reference list (PESDA 2022 [5], EDSNA 2024 [3], IPCC 2006 [39]). To support full replicability, the reproducibility package is provided as Supplementary Materials and comprises: (i) the machine-readable parameter files (01_parameters.csv) listing every value with its source and uncertainty range; (ii) the four scenario-rollout definitions and the SOS2 breakpoint coordinates; (iii) the Latin-hypercube design specification (12 parameters, ranges and seed = 42) enabling exact re-generation of the 10,000-run sample; (iv) the processed Monte-Carlo outputs and the sensitivity, probability-robustness and distributional-robustness tables; and (v) the GAMSPy/Python code implementing the formulation of Section 4. These materials are additionally available from the author on reasonable request.

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Conflicts of Interest: The author declares no conflict of interest.

Appendix A. Parameter Source Audit (Summary)

The model is calibrated to PESDA 2022 [5], the YPEN SMPE 2025 plan [6], IPCC 2006 Vol.5 [39] and eleven confirmed 2024 EDSNA operational files [3]. All 43 parameter groups (>200 indexed values) are classified into four source-quality categories (Table A1). The complete parameter-by-parameter audit, the SOS2 breakpoint and scenario-rollout tables, the full KPI definitions and all figures at full resolution are provided in the Supplementary Materials.

Table A1. Parameter source-quality classification (43 groups, >200 indexed values).

Category	Count	Definition
Validated (V)	22	Exact value from a PESDA formal table or an uploaded 2024 EDSNA operational file.
Literature (L)	13	Specific peer-reviewed paper or official EU/EIB/IPCC publication; value within documented range.
Estimated (E)	5	Documented derivation from a primary-source total via a standard financial/engineering formula.
Sensitivity (S)	4	Genuinely uncertain; covered by the Monte-Carlo and factorial scans.

Appendix B. Scalability and Comparison with Alternative Methods

To characterise algorithmic behaviour beyond the deployed Attica instance, the deterministic-equivalent MILP is solved under a growing scenario set $|S| \in \{4, 8, 16, 32, 64\}$, with rollout trees refined by interpolating the α -trajectories between the slow and full extremes and assigning uniform probabilities (Table A2). The equation and variable counts grow linearly in $|S|$ (8464 $\rightarrow$ 131,644 equations; 25,855 $\rightarrow$ 410,395 variables), because only the scenario-indexed Stage-2 flow block scales, while the binary count—which governs branch-and-bound difficulty—stays constant at 156, since the here-and-now investment decisions are scenario-independent by construction. Solve time to a 0.5% gap grows only mildly, from 1.1 s at $|S| = 4$ to 47 s at $|S| = 64$, and the expected NPV is stable (€2771–2774 M) across granularities. Scenario refinement is therefore cheap; the wall-clock cost of the study is dominated by the 10,000 independent Monte-Carlo solves, which are embarrassingly parallel. The physical Attica system has a fixed real facility set; facility scaling would raise the binary count proportionally to $|K_{\text{new}}|$, and the Monte-Carlo dimensionality (12 $\rightarrow$ 24) affects only the number of independent solves, not the per-solve size.

Table A2. Deterministic-equivalent MILP scaling with the scenario set (CPLEX 22.1, 0.5% gap).

$ S $	Equations	Variables	Binaries	Solve Time (s)	Expected NPV (€ M)
4	8464	25,855	156	1.0	2771
8	16,676	51,491	156	2.4	2772
16	33,100	102,763	156	5.0	2770
32	65,948	205,307	156	14.6	2773
64	131,644	410,395	156	36.8	2774
128	263,036	820,571	156	84.2	2770
256	525,820	1,640,923	156	282.3	2770
512	1,051,388	3,281,627	156	756.6	2770

Three method comparisons follow. Against a deterministic MILP, the expected-value solution is the VSS reference; here $VSS \approx 0$ (Section 5.3) because the optimal Stage-1 capacity is a robust corner solution (Section 5.9), so the deterministic solution is near-optimal under uncertainty. Against robust optimisation, a min–max counterpart over the rollout set returns the same Stage-1 vector, because the maximum-capacity decision is optimal under the worst-case rollout as well; a budgeted-uncertainty robust variant is left to future work. Against decomposition, Benders/L-shaped or progressive-hedging schemes become the methods of choice well above the scales of Table A2 (thousands of scenarios), but are unnecessary at the deployed scale, where even $|S| = 64$ solves in under a minute.

Facility scaling. To characterise the axis that governs integer difficulty, the generic mechanical-treatment (MAA) facility family is replicated $\times 1\text{--}\times 8$, each clone inheriting the transport, processing, capacity and emission parameters of its base facility, with the scenario tree held fixed at $|S| = 4$ so that only the facility/binary block grows. These are algorithmic scaling stress-tests, not proposed real facilities. The resulting scaling behaviour is reported in Table A3.

Table A3. Facility scaling at fixed $|S| = 4$ (synthetic stress-test instances; CPLEX 22.1, 0.5% gap).

Facility Scale	MAA Candidate Sites	Binaries	Equations	Variables	Solve Time (s)	Expected NPV (€ M)
×1 (Attica)	6	156	8464	25,855	0.7	2767
×2	12	228	8818	33,991	0.9	2760
×4	24	372	9526	50,263	3.5	2756
×8	48	660	10,942	82,807	7.2	2760

In contrast to the scenario axis (Table A2), the binary count grows with the candidate set ($156 \rightarrow 660$) and the solve time rises with the integer block ($0.7 \rightarrow 7.2$ s). The number of candidate facilities is therefore the axis that governs branch-and-bound difficulty and on which decomposition or warm-started rolling solves would be introduced at national scale.

Uncertainty-dimension scaling. Expanding the Latin-hypercube design from the 12 headline parameters to $D \in \{12, 24, 48\}$ (adding idiosyncratic per-facility, per-corridor and per-stream cost and emission multipliers) leaves the per-solve MILP identical—the sampling dimension does not touch the model—and preserves the sensitivity ordering. The resulting scaling behaviour is reported in Table A4.

Table A4. Uncertainty-dimension scaling of the Monte-Carlo layer (uniform marginals, $N = 2000$; 1999 at $D = 24$).

Dimensions D	Equations	Variables	Binaries	Mean NPV (€ M)	Convergence N	q (Carbon)	q (Landfill Tax)
12	8464	25,855	156	3520	500	0.890	0.353
24	8464	25,855	156	3512	500	0.891	0.347
48	8464	25,855	156	3509	500	0.856	0.343

The per-solve instance is identical across D ; the sample size at which the mean-NPV estimate stabilises does not grow appreciably with D (≈ 500 throughout) because the carbon price dominates the output variance, and it remains the top-ranked driver at every D (q $0.890 \rightarrow 0.856$).

Quantitative solution-strategy comparison. Table A5 compares the proposed monolithic extensive form against (i) a deterministic expected-value problem (EVP) and (ii) Benders decomposition. The EVP solves in 1.1 s; fixing its first-stage decision and evaluating it under the four-scenario tree gives an expected NPV of €2768.6 M versus the stochastic optimum €2767.5 M, so the value of the stochastic solution is $VSS = -€1.2$ M (-0.04%), within solver tolerance of zero—a computed result reflecting the robust corner solution of Section 5.9, which the deterministic model cannot itself establish. CPLEX’s Benders algorithm does not support the SOS2 economies-of-scale representation directly (it rejects models containing SOS constraints); we therefore applied it to a binary-equivalent reformulation of the SOS2 block—segment-selector binaries that enforce the same at-most-two-adjacent condition—verified to reproduce the SOS2 optimum exactly at a tight gap (€2770.25 M at both). On that equivalent model, automatic Benders decomposition runs but is slower than the monolithic extensive form at every scenario count tested ($1.4\text{--}1.9\times$; 751.5 s versus 427.7 s at $|S| = 512$), with no crossover through $|S| = 512$. The here-and-now integer block is small and fixed (≈ 160 binaries) while only the continuous recourse grows, so the extensive form’s single branch-and-bound tree is not improved by Benders’ cut-generation overhead at these scales. A purpose-built L-shaped scheme [17] exploiting the scenario block structure is identified as the extension most likely to pay off at substantially larger scenario counts.

Table A5. Solution-strategy comparison: solve time (s) at a 0.5% gap on the binary-equivalent reformulation of the SOS2 block (identical optimum). All solves reach the optimum within tolerance. Deterministic EVP: 1.1 s, VSS = −€1.2 M (−0.04%). The monolithic extensive form is faster than Benders at every tested scale.

Strategy	S = 8	S = 64	S = 256	S = 512
Extensive form—solve time (s)	1.3	21.6	177.0	427.7
CPLEX automatic Benders—solve time (s)	1.9	30.5	333.9	751.5

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