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Multi-Objective Optimization of Gas Compression, Flare Recovery, and Production Efficiency in Mature Oil and Gas Fields

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Abstract

Mature oil fields face falling reservoir pressure, rising gas-oil ratios and compression systems sized for earlier conditions. As a result, usable gas is often flared. This study develops a multi-objective framework that jointly optimizes booster compression capacity, compressor driver type, separator suction pressure, flare gas recovery capacity and lift gas rate. The objectives are incremental net present value, cumulative oil production and cumulative greenhouse gas emissions over a ten-year horizon. The framework couples well and gas-lift performance, multistage compression, compressor availability, flare header flow variability, emissions and discounted cash flow. It is applied to a representative 24-well gas-lifted field using literature-based inputs, not field data. NSGA-II recovered 99.8 percent of the hypervolume of an exhaustive search of 29,250 designs. Maximizing value alone raised oil output by 39 percent but nearly doubled emissions, because added lift gas and lower suction pressure increased both flaring and engine fuel use. A compromise design with four electric-driven units, a 75 psia suction pressure and 3 MMscfd of flare gas recovery kept 79 percent of the maximum value gain and raised oil output by 34 percent, while cutting emissions by 58 percent and flaring by 91 percent. Flare gas recovery was the cheapest abatement lever, at about USD 7 per tonne, and a carbon price of USD 50 per tonne made it part of the value-maximizing design.

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1. Introduction

A large and growing share of world oil supply comes from fields that are past their production peak. In these mature fields, reservoir pressure declines, water cut rises and the gas-oil ratio increases as reservoir pressure falls below the bubble point, so that the surface facilities built for the plateau period must handle more gas and water for each barrel of oil ^[1-3]. Analyses of global super-giant fields show that energy productivity falls steadily with field age ^[2], and field-level life cycle assessment of 8,966 fields in 90 countries found that the upstream carbon intensity of crude oil varies by more than an order of magnitude, with flaring, venting and fugitive emissions among the largest contributors ^[1, 4]. The same studies show that oil extraction becomes markedly more emissions-intensive as fields age, because more energy is spent lifting, separating and compressing fluids for each barrel recovered ^[1, 5, 6].

Gas handling is the point at which these trends meet. Associated gas must be compressed for sale, reinjection, fuel or gas lift, and when compression capacity, takeaway capacity or gas prices are insufficient, operators flare it ^[7-9]. Flaring wastes a resource, emits carbon dioxide, unburned methane, black carbon and nitrogen oxides ^[10-12], and has been linked with adverse respiratory

health outcomes in exposed populations [13]. Field measurements show that flare combustion efficiency can fall well below design values at low flow rates and in crosswinds, so that methane slip from flares is often larger than inventories assume [14–17]. At the same time, the compressors that keep gas out of the flare are themselves major energy users and sources of emissions, through engine fuel combustion, methane slip in exhaust and venting from rod packing and blowdowns [18–21].

In mature fields the compression, flaring and production problems are coupled. Lowering separator and wellhead pressure increases well inflow and can restore wells that would otherwise load up with liquids [22–24], but it raises the compression ratio and the power needed to deliver gas to sales or injection pressure [25, 26]. Increasing lift gas raises oil rates in gas-lifted wells up to an economic optimum, but every unit of lift gas must be recompressed [27–29]. Flare gas recovery systems capture low-pressure gas that would otherwise be flared, but the recovered gas must also be compressed and requires spare capacity in the booster system [30–32]. Replacing gas engine drivers with electric motors removes on-site combustion and methane slip, but its net benefit depends on the carbon intensity of grid power and on capital and power costs [33–35]. Each of these levers changes production, cost and emissions at once, and the best combination depends on prices, carbon costs and reservoir behaviour. The same choices also affect the reliability of the gas infrastructure, which risk-based process engineering treats as a design objective in its own right [36, 37].

Most published optimization studies address these levers separately. Gas-lift allocation has been optimized for oil rate or profit [38–40], compressor stations for fuel use and load sharing [41–43], flare gas recovery for techno-economic and environmental performance [44–46] and field development for net present value under uncertainty [47–49]. Fewer studies treat compression, flare recovery and production together as a multi-objective design problem, and fewer still quantify the trade-off between oil recovery, economic value and greenhouse gas emissions over the remaining life of a mature field [50–52].

This paper addresses that gap. It makes four contributions. First, it formulates an integrated model of a mature gas-lifted field that couples well inflow and gas-lift performance, multistage compression power, compressor availability, flare header flow variability, flare gas recovery, flaring and driver emissions, and discounted cash flow. Second, it solves a three-objective problem in incremental net present value, cumulative oil and cumulative greenhouse gas emissions with the NSGA-II algorithm and verifies the Pareto front against an exhaustive search. Third, it decomposes the emissions and economic effects of individual levers and identifies their abatement costs. Fourth, it tests how carbon prices, commodity prices, flare efficiency, grid intensity and reservoir uncertainty change the preferred designs. Section 2 reviews the literature, Section 3 describes the model and optimization, Section 4 presents the results, Section 5 discusses implications and limitations and Section 6 concludes.

2. Literature Review

This section reviews five bodies of work that the framework draws on: gas compression and its optimization in production and transport systems; liquid loading and deliquification in maturing wells; gas lift and integrated production

optimization; flare gas recovery, utilization and flare emissions; and multi-objective optimization and the carbon intensity of oil production. It closes by identifying the gap that this study addresses. The review emphasizes studies that quantify trade-offs, because the purpose of the framework is to make the trade-offs between production, value and emissions explicit rather than to optimize any one of them in isolation [4, 50, 51]. Studies were selected for their relevance to mature onshore and offshore fields, with emphasis on work published since 2010.

2.1. Gas Compression in Production and Transport Systems

Compression is the largest energy consumer in most gas handling systems. Standards such as API 617 for centrifugal compressors and API 614 for lubrication and sealing systems define design and reliability requirements [53, 54], and handbooks describe the thermodynamics of multistage compression with intercooling [25, 26]. Optimization of compressor stations has been formulated as mixed-integer nonlinear programming and its continuous reformulations [41], as fuel-consumption minimization by genetic algorithms [55] and as multi-objective design of compression power trains [56]. Load sharing among parallel compressors has been optimized using online performance tracking [42], modifier adaptation [57], Gaussian-process approximations of compressor maps [58], swarm algorithms [43] and coordinated control of parallel and serial stations [59, 60], building on real-time optimization methods whose reliability depends on plant-model mismatch [61–63]. Operational and maintenance planning of compressor networks [64], detection of abnormal energy consumption [65], compressor washing economics [66] and energy savings in compressed air systems [67] show the value of treating compression energy as a controllable variable.

Pipeline network studies extend these ideas to transport systems. Multi-objective design and operation of gas transmission networks have balanced cost, throughput and emissions [51, 68, 69], including techno-economic and environmental optimization [50], ant colony approaches [70, 71], simulation-based improvement of national networks [72], distribution networks with future extensions [73], transient models [74, 75], flow model comparisons [76] and coordination with power networks [77]. Energy consumption models for carbon dioxide transport [78, 79] and cogeneration systems assessed for availability [80] use similar formulations. Compressor performance can be predicted from data using neural networks [81, 82], part of a wider use of machine learning and data-driven methods in industrial automation and process control [83], and surge control remains a central constraint on operating range [84–86].

Availability of reciprocating compressors is limited mainly by valve, packing and ring failures. Machine learning has been applied to fault diagnosis from indicator diagrams, vibration and acoustic emission [87–89], an application of the predictive maintenance and condition monitoring practices developed for critical power and energy infrastructure [90], including support vector machines [91], convolutional networks with multisource data [92, 93], local mean decomposition with stacked autoencoders [94], system characteristics for valve leakage [95], pattern recognition of valve cracks [96], linear discrimination of p-V diagrams [97], hidden Markov trees with neural networks [98], pressure-based nondestructive methods [99] and experimental studies of

typical faults^[100]. Vibration monitoring in operating fleets has also been reported^[101], and interpretable machine learning has been used for early failure prediction in distributed energy assets^[102]. These studies show that compressor outages are frequent enough to matter for flaring, a point the present model captures through unit availability. Electrification and variable speed drives are increasingly used to reduce compressor emissions. Experience with adjustable-speed drives in pipeline service^[103], technical and economic considerations for variable speed drives with electric motors^[35], a case study on energy efficiency and emissions reductions from variable speed drives^[34] and the replacement of gas engine drivers by electric motors in upstream service^[33] show that the benefit depends on power costs and grid emissions. Advances in power electronics and converter topologies have improved the efficiency of such drives^[104]. Methane emissions from compressor rod packing and from blowdowns when compressors are taken off line are well documented^[18, 19, 105], and the historical inventory of methane emissions from the natural gas industry identified compressors as a leading source^[20].

2.2. Liquid Loading and Deliquification in Maturing Wells

As reservoir pressure falls, gas velocity in the tubing drops below the rate needed to lift liquids, and wells load up and die. The classic droplet model of Turner and colleagues^[106] and its later revisions^[107–109] define the critical rate, and many refinements have been proposed for deviated and horizontal wells^[110–113], transitional flow^[113], droplet size^[114], energy conservation^[115], foam^[116], condensate wells^[117] and inclined wells^[118–121]. Reviews compare these models^[122, 123], and dynamic and transient models show how loading develops over time^[124–128]. Practical guidance covers the diagnosis and remediation of loading^[22, 23, 129], decision matrices for lifting options^[130] and foaming agents^[131]. These studies are relevant to compression design because lowering wellhead pressure is one of the most effective deliquification measures. Wellhead and booster compression increase the drawdown and gas velocity, delaying the onset of loading and extending well life, but at the cost of compression power^[22, 23, 129]. The present framework represents this effect through the dependence of well inflow on separator and wellhead pressure.

2.3. Gas Lift and Integrated Production Optimization

Gas lift is the dominant artificial lift method in many mature fields because it tolerates sand, gas and deviated wells^[132, 133]. The allocation of a limited lift gas supply among wells has been studied extensively. Surveys^[27] and formulations based on equal marginal returns, mixed-integer and piecewise-linear models^[29, 38, 39], global optimization^[134], metaheuristics^[28, 135–137], economic allocation with different performance curve types^[138] and hypervolume-based multi-objective methods^[52, 139] have been proposed. Neural network models of gas-lift performance^[140–143] provide fast surrogates. Field applications include automated optimization and diagnostics^[144–146], closed-loop optimization^[147], intelligent gas-lift valves^[148], unconventional wells^[149], offshore heavy crude^[150], the Orenburg field^[151], high carbon dioxide associated gas^[152], intermittent lift^[153, 154], wellhead pressure and water cut effects^[24], artificial intelligence in Middle Eastern fields^[155] and model predictive control^[156, 157]. Artificial lift selection

and timing have been addressed with fuzzy logic^[132], physics-informed data analytics^[158], field testing in redevelopment projects^[159], visual analytics^[160], evaluations in the Niger Delta^[161] and integrated approaches^[162], and riser slugging control illustrates the coupling of wells and facilities^[163].

Integrated production optimization couples reservoirs, wells, pipelines and facilities. Early work integrated surface networks with reservoir models at Prudhoe Bay^[164], and later studies optimized oil rate allocation^[40], piecewise-linear and decomposition models^[165], pressure and routing constraints^[166], compressor scheduling^[167] and corporate integrated field management programmes^[168]. Multiphase flow correlations such as Beggs and Brill^[169] underlie these models. Decline curve analysis remains the standard tool for production forecasting, from the original hyperbolic formulation^[170] and its review^[171] to Bayesian^[172] and machine learning methods^[173–179], and similar predictive modeling frameworks are used to forecast energy yield in the power sector^[180]. Studies of the Bakken show how productivity and recovery evolve^[181].

2.4. Flare Gas Recovery, Utilization and Flare Emissions

Flare gas recovery systems compress gas from the flare header and return it to the process, typically using liquid ring or reciprocating compressors^[30, 182, 183]. Techno-economic, environmental and reliability assessments compare recovery technologies^[31, 32, 45], exergy analysis of natural gas liquids recovery and the choice of exergy efficiency definition for low temperature processes guide the efficient use of recovered gas^[184, 185], and economic-environmental optimization sizes recovery systems^[44, 186]. Reviews of recovery potential in Iran^[187] and of associated gas technologies^[188], case studies in Tunisia^[183] and the United Arab Emirates^[182] and reviews of recovery technologies for energy security and resource efficiency^[46] show a wide range of costs and benefits. Recovered gas can be used for power generation in gas turbines^[189, 190] or reciprocating engines adapted for low methane number fuels^[191, 192], for rig power in shale operations^[193], for small-scale liquefied natural gas^[194], for natural gas liquids recovery^[195], or for syngas and other products^[196, 197]. Industry guidance for greenhouse gas reduction projects^[198], mitigation options in Colombian fields^[199, 200], techniques for gas emission reduction^[201], flare and vent mitigation case studies^[202] and greenhouse gas emissions from North American conventional crudes^[203] provide context, and energy management and dynamic simulation reduce flaring in abnormal operations and start-ups^[204–206]. Process studies of acid gas removal show how energy use in gas treatment can be reduced^[207].

Flare emissions depend strongly on combustion efficiency. Early studies of flare combustion efficiency^[208, 209] were followed by detailed measurements at low flow conditions^[12, 14, 15], methodologies for measuring efficiency and species emissions^[210], comparisons of remote sensing and extractive sampling^[17], validation of large eddy simulations^[211], and flame downwash studies^[212]. Airborne measurements at offshore facilities in the North Sea, Southeast Asia and elsewhere have quantified flaring efficiencies, methane and volatile organic compound emissions^[16, 213–217]. Emission factors for industrial flares^[218], inventories for offshore production in the Gulf of Mexico^[219] and the United Kingdom continental shelf^[220], global gridded methane inventories^[221], constraints on fugitive emission rates^[222],

global black carbon and particulate inventories^[10] and assessments of short-lived pollutant impacts^[11] place flaring in its wider emissions context. Safety requirements for flares are also important when recovery systems are added^[223]. International agencies track flaring trends and definitions^[7, 8], and outlooks for offshore energy highlight the role of gas utilization^[224].

2.5. Multi-Objective Optimization and Carbon Intensity of Oil Production

Multi-objective evolutionary algorithms are the standard tool for engineering design problems with conflicting objectives. Non-dominated sorting^[225] and its elitist successors^[226], the strength Pareto approach^[227], Pareto archived evolution strategies^[228], decomposition-based methods^[229], reference-point methods for many objectives^[230–232], generalized differential evolution^[233–235] and archiving methods that combine convergence and diversity^[236] have been compared in benchmark studies^[237], and performance assessment of optimizers relies on indicators such as hypervolume^[238]. The epsilon-constraint method offers an exact alternative for small problems^[239], and TOPSIS is widely used to choose a compromise from a Pareto set^[240]. Concept selection under uncertainty using Pareto frontiers^[241] and Pareto regions^[242] extends these methods to decisions. Open-source libraries such as pymoo make the methods accessible^[243].

In petroleum engineering, multi-objective methods have been applied to waterflooding and well control^[244–246], oilfield development under geological uncertainty^[49, 247], non-vertical well placement^[248], surrogate-assisted production optimization^[249–254], robust optimization with stochastic gradients^[255–258] and proxy models^[259–261]. Hierarchical and robust formulations balance short- and long-term value^[47, 48, 262], closed-loop reservoir management updates models as data arrive^[263, 264], and adjoint methods^[265], informed optimization^[266], joint optimization of project life and controls^[267], derivative-free methods^[268] and surrogate treatments^[269, 270] improve efficiency. Representative model selection^[271, 272], well placement under uncertainty^[273–276], mature field opportunity indices^[277–279], multifidelity methods^[280], Gaussian-process infill criteria^[281], reduced-order models^[282], transfer learning for unconventional operations^[283] and robust optimization of thermal recovery^[284] complete this toolbox.

A separate literature quantifies the carbon intensity of oil production. Field-level models estimate emissions from extraction, processing, flaring and venting^[4, 285, 286], including the influence of field age^[1], net energy and energy return on investment^[2, 3, 5, 6], embodied emissions in materials^[287], fracturing fuel combustion^[288], oil sands^[289, 290], uncertainty and reproducibility of life cycle models^[291, 292], the United States petroleum baseline^[293], refining^[294], jet fuel^[295], China's crude supply^[296], marginal oils^[297], and flaring by field^[9]. Solar energy in the petroleum sector^[298], integrated solar combined cycles^[299, 300], electricity-intensive facility design under price uncertainty^[301], carbon capture process optimization^[302], carbon dioxide enhanced oil recovery^[303–305] and climate-wise choices among oil resources^[286] illustrate how emissions constraints enter design. Offshore studies have optimized energy efficiency through site-scale integration, steam bottoming cycles,

combined cycles and heat recovery^[306–310], and the Norwegian experience shows how a carbon tax influences upstream emissions^[311]. Carbon taxes affect energy use and operating decisions in waterflooded oil fields^[312], regulatory inefficiency can raise costs in the Bakken^[313], carbon taxes have been built into production planning frameworks^[314], and the International Energy Agency has examined how net zero transitions change the investment choices of oil and gas companies^[315]. Obligations to disclose greenhouse gas emissions under environmental, social and governance reporting regimes add a further reason for operators to quantify flaring and driver emissions^[316].

2.6. Research Gap

Three gaps emerge. First, compression, flare recovery and gas-lift studies are usually conducted separately, although in mature fields the three compete for the same compression capacity and gas^[27, 44, 167]. Second, multi-objective studies in petroleum engineering mostly balance economic value against recovery or risk, and rarely include greenhouse gas emissions from flaring, drivers and venting as an explicit objective^[49, 52, 244]. Third, carbon intensity studies quantify emissions at field scale but do not optimize the design choices that determine them^[1, 4, 9]. The framework developed in this study addresses these gaps by optimizing compression, driver type, suction pressure, flare recovery and lift gas together against value, production and emissions objectives, and by testing the robustness of the resulting designs under price, policy and reservoir uncertainty.

3. Methodology

This section describes the integrated field model, the optimization problem and the scenario and uncertainty analyses. The model represents a mature onshore oil field, typical of conventional gas-lifted fields in the Permian Basin of West Texas, over a ten-year horizon^[1, 6, 181]. All inputs are representative values taken from or consistent with the literature cited in this section; they are not field data, and the results should be read as a demonstration of the framework and of the direction and relative size of the trade-offs rather than as predictions for a specific asset^[291, 292]. The model was implemented in Python, and the optimization used the NSGA-II implementation in pymoo^[226, 243].

3.1. Framework Overview

Figure 1 shows the system. Twenty-four gas-lifted wells produce oil, water and associated gas to a production separator whose pressure sets the compressor suction pressure. Booster compressors deliver gas to sales at 900 psia and to the gas-lift distribution system at 1,300 psia. Lift gas returns with the produced fluids and is recompressed, so lift gas and associated gas compete for the same compression capacity, as in integrated field models^[164, 166, 167]. Low-pressure gas from storage tanks, purge and relief valve leakage is routed to the flare header and is flared unless a flare gas recovery system returns it to compressor suction^[30, 182, 183]. Gas exceeding the available compression capacity, including gas displaced by compressor outages, is flared^[19, 101]. Compressor drivers are either gas engines, which burn fuel gas and emit methane in their exhaust, or electric motors supplied from the grid^[33, 34].

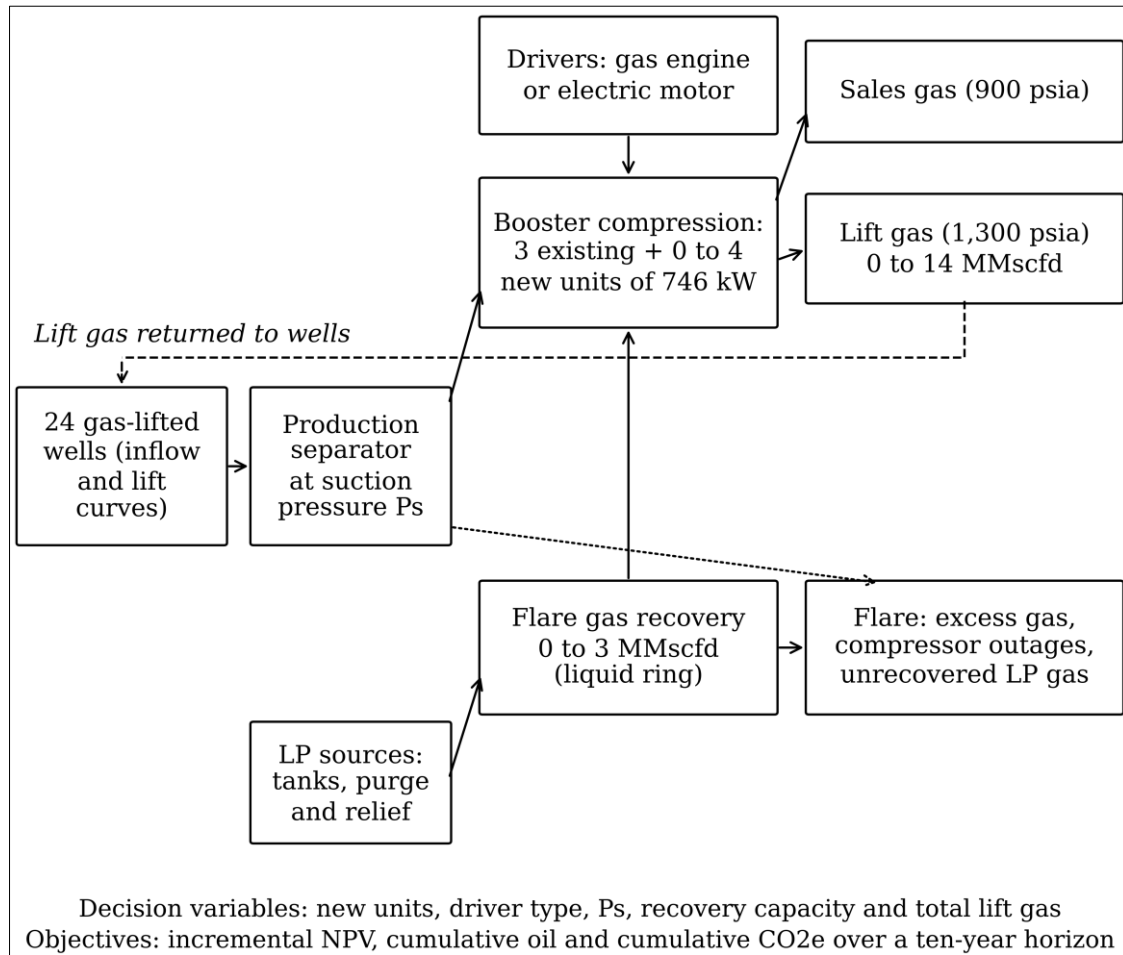


Fig 1: Integrated system representation of the mature field, showing wells, separation, booster compression, gas lift, flare gas recovery and flaring, with the decision variables and objectives of the optimization.

Five decision variables describe the design: the number of new 1,000 hp (746 kW) compressor units added to the three existing units (0 to 4); the driver type for the whole station (gas engine or electric motor); the separator suction pressure (40 to 250 psia); the flare gas recovery capacity (0 to 3 MMscfd); and the total lift gas rate (0 to 14 MMscfd), which is allocated optimally among wells each year. Three objectives are evaluated over the horizon: incremental net present value relative to the current operation, cumulative oil production and cumulative greenhouse gas emissions in carbon dioxide equivalent [4, 50, 51].

3.2. Well Inflow and Gas-Lift Performance

Each well follows a linear inflow performance relationship, which is adequate for the moderate drawdowns of gas-lifted wells in a depleted reservoir [24, 27]:

$$q_{L,i} = J_i(P_r(t) - P_{wf,i}) \quad (1)$$

where $q_{L,i}$ is the liquid rate of well i (bbl/d), J_i is its productivity index (bbl/d/psi), $P_r(t)$ is reservoir pressure and $P_{wf,i}$ is the flowing bottomhole pressure. The bottomhole pressure is the sum of wellhead pressure, the hydrostatic head of the gasified fluid column and a frictional term that grows with lift gas rate, which reproduces the characteristic maximum of the gas-lift performance curve [24, 28, 138]:

$$P_{wf,i} = P_{wh} + \left[g_{min} + (g_w - g_{min}) \exp\left(-\frac{GLR_i}{GLR_c}\right) \right] D_i + f L_i D_i \quad (2)$$

where g_w and g_{min} are the gradients of the unaerated liquid and of a fully aerated column (psi/ft), GLR_i is the total gas-liquid ratio including formation and lift gas (scf/bbl), GLR_c is a characteristic ratio, D_i is well depth (ft), f is a friction coefficient and L_i is the lift gas rate of the well (MMscfd). The wellhead pressure equals the separator pressure plus a flowline pressure drop of 40 psi. Because $P_{wf,i}$ depends on $q_{L,i}$ through the gas-liquid ratio, the two equations were solved for each well by bisection, which guarantees a unique root because the residual is monotonic in the liquid rate [166, 169].

Reservoir depletion and fluid changes are represented by exponential pressure decline and linear growth in water cut and gas-oil ratio, consistent with the behaviour of mature fields below the bubble point [1, 2, 170]:

$$P_r(t) = P_{r0} e^{-\delta t}, \quad WC_i(t) = WC_{0,i} + \omega t, \quad R_s(t) = R_{s0}(1 + \gamma t) \quad (3)$$

where δ is the pressure decline rate, ω the annual increase in water cut and γ the annual relative increase in gas-oil ratio.

The total lift gas is allocated among wells in each year by the equal-marginal-return rule, implemented as a greedy allocation in increments of 0.025 MMscfd on the concave

envelope of each well's performance curve, which is optimal for concave curves [27, 29, 39]. Table 1 lists the reservoir and well parameters.

Table 1: Reservoir, well and fluid parameters of the representative field.

Parameter	Value
Number of gas-lifted wells	24
Productivity index (bbl/d/psi)	Uniform 0.6 to 1.6
Well depth (ft)	Uniform 6,500 to 8,500
Initial reservoir pressure (psia)	2,300
Reservoir pressure decline rate (per year)	0.018
Initial water cut	Uniform 0.55 to 0.80
Water cut increase (per year)	0.012
Initial gas-oil ratio (Mscf/bbl)	2.2
Gas-oil ratio growth (per year, relative)	0.10
Liquid and aerated gradients (psi/ft)	0.44 and 0.15
Characteristic gas-liquid ratio (scf/bbl)	600
Flowline pressure drop (psi)	40
Lift gas supply limit (MMscfd)	14

3.3. Compression Power and Capacity

The specific power required to compress one MMscfd of gas from suction pressure P_1 to discharge pressure P_2 was computed from the isentropic multistage relation with intercooling to suction temperature [25, 26, 56]:

$$w(P_1, P_2) = \frac{\dot{m}}{\eta} \frac{k}{k-1} \frac{ZRT_1}{M} N \left[\left(\frac{P_2}{P_1} \right)^{\frac{k-1}{Nk}} - 1 \right], \quad N = \left\lceil \frac{\ln(P_2/P_1)}{\ln 4} \right\rceil \quad (4)$$

where $\dot{m}$ is the mass flow per MMscfd, η is the overall efficiency (0.78), k is the heat capacity ratio (1.27), Z the compressibility factor (0.95), T_1 the suction temperature (310 K), M the molar mass (20 kg/kmol) and N the number of stages, limited to a ratio of 4 per stage. At a suction pressure of 150 psia the specific power is 106 kW per MMscfd for lift gas and 86 kW per MMscfd for sales gas, rising to 138 and 124 kW per MMscfd at 75 psia. The available compression power is the number of running units multiplied by 746 kW. Lift gas has priority for compression because it sustains oil production, and associated and recovered gas is compressed to sales with the remaining capacity, which reflects common operating practice in gas-lifted fields [27, 167].

3.4. Compressor Availability and Flaring

Compressor outages are a major cause of flaring in practice [8, 19, 87]. Each unit was assumed to be available with probability A independently of the others, 0.95 for gas engine drives and 0.975 for electric motor drives, which reflects the lower maintenance burden of motors [33, 35, 89]. Treating the running state of redundant units as a binomial outcome is standard practice in reliability engineering and failure analysis of complex systems [36, 317], and plant uptime also depends on the availability of spare parts and materials [318, 319]. The probability that k of n units are running is

$$\Pr(k) = \binom{n}{k} A^k (1-A)^{n-k} \quad (5)$$

and the expected annual flare volume is the sum over these states of the gas that cannot be compressed, plus the low-pressure gas that is not recovered [7, 9]:

$$V_f = \sum_{k=0}^n \Pr(k) \left[G_a^{(k)} + R - \min \left(G_a^{(k)} + R, \frac{kW_u - L^{(k)}w_L}{w_s} \right) \right] + (Q_{LP} - R) \quad (6)$$

where $G_a^{(k)}$ is the associated gas rate in state k , R is the recovered low-pressure gas, W_u is the power of one unit, $L^{(k)}$ is the lift gas that can be compressed in state k , w_L and w_s are the specific powers for lift and sales gas and Q_{LP} is the mean low-pressure flare header flow. When a unit is down and capacity is insufficient for the lift gas, the lift gas is reduced and oil production falls accordingly, so outages affect both flaring and production.

3.5. Flare Gas Recovery

Low-pressure flare header flow is highly variable because it combines continuous purge and leakage with intermittent tank flashing and relief events [30, 205, 206]. It was represented as a lognormal random variable X with mean 1.3 MMscfd and coefficient of variation 0.6. A recovery system of capacity C_F recovers the part of the flow below its capacity when it is available, so the expected recovered gas is

$$R = A_F E[\min(X, C_F)] \quad (7)$$

where A_F is the availability of the recovery system (0.95) [31, 32, 44]. The expectation was evaluated by numerical quadrature. Because of the long upper tail of the flow distribution, recovery shows diminishing returns: 1.0, 2.0 and 3.0 MMscfd of capacity recover 0.83, 1.13 and 1.21 MMscfd on average. Recovered gas enters the compressor suction and is sold if there is spare capacity, and it is flared when compression is unavailable, which captures the dependence of flare recovery on compression capacity [182, 183].

3.6. Greenhouse Gas Emissions

Emissions were computed for three sources: flaring, compressor drivers and compressor venting. Flared gas was assumed to contain 80 percent methane by volume and to emit 58 kg of carbon dioxide per Mscf when fully combusted. With combustion efficiency η_f , the flaring emissions are ^[208, 210, 218]

$$E_f = V_f [e_{CO_2} \eta_f + m_{CH_4} (1 - \eta_f) GWP_{CH_4}] \quad (8)$$

where e_{CO_2} is the carbon dioxide emitted per Mscf burned, m_{CH_4} the methane mass per Mscf (15.4 kg) and GWP_{CH_4} the 100-year global warming potential of fossil methane

(29.8). The base combustion efficiency was 98 percent, and 91 percent was tested as a sensitivity because field measurements have found lower efficiencies than design values ^[14, 16, 17]. Gas engine drivers were assumed to consume 7.5 MMBtu of fuel per MWh of shaft work and to emit 53.06 kg of carbon dioxide and 0.57 kg of methane per MMBtu ^[198, 218], and fuel gas reduces gas sales. Electric drivers were charged with a grid emission factor of 0.37 t of carbon dioxide per MWh, with 0.20 t per MWh tested as a lower-carbon grid of the kind expected as renewable penetration rises ^[33, 301, 320]. Venting from rod packing and blowdowns was taken as 10 t of methane per reciprocating unit per year for both driver types ^[18, 19, 105]. Table 2 summarizes the compression, flaring and emissions parameters.

Table 2: Compression, flare gas recovery and emissions parameters.

Parameter	Value
Existing compressor units	3 x 746 kW (gas engine)
New units	0 to 4 x 746 kW
Unit availability, gas engine and electric	0.95 and 0.975
Sales and lift gas discharge pressure (psia)	900 and 1,300
Mean low-pressure flare header flow (MMscfd)	1.3 (lognormal, CV 0.6)
Flare gas recovery availability	0.95
Flare combustion efficiency	0.98 (0.91 sensitivity)
Carbon dioxide from combustion (kg/Mscf)	58
Methane in flared gas (kg/Mscf)	15.4
Global warming potential of methane (100-year)	29.8
Engine fuel rate (MMBtu/MWh)	7.5
Engine emission factors (kg/MMBtu)	53.06 CO ₂ ; 0.57 CH ₄
Grid emission factor (t CO ₂ /MWh)	0.37 (0.20 sensitivity)
Compressor venting (t CH ₄ per unit-year)	10

3.7. Economic Evaluation

Net present value was computed over the ten-year horizon with annual cash flows discounted at 10 percent to mid-year, with capital expenditure at the start of the first year ^[48, 267]:

$$NPV = -C_0 + \sum_{t=0}^9 \frac{p_o \nu Q_{o,t} + p_g S_t - c_L Q_{o,t} - c_W W_t - O_t - p_e E_t^{el} - p_c E_t}{(1+r)^{t+0.5}} \quad (9)$$

where p_o is the oil price, ν the net revenue fraction after royalties and transport, $Q_{o,t}$ the annual oil production, p_g the gas price, S_t the sales gas volume, c_L and c_W the lifting cost per barrel of oil and the water handling cost per barrel, W_t

the water volume, O_t the fixed operating cost of compressors and recovery, p_e the power price, E_t^{el} the electricity purchased, p_c the carbon price and E_t the emissions. The objective is the incremental net present value ΔNPV relative to the current operation. Table 3 lists the economic parameters. The gas price of USD 2.5 per Mscf reflects the weak and sometimes negative prices at the Waha hub in West Texas caused by pipeline takeaway constraints, which have been a central driver of flaring in the Permian and Bakken basins ^[8, 9, 313]. Capital costs are budgetary estimates; actual costs for compressor packages and recovery systems depend on procurement strategy and on supply chain risk in gas processing projects ^[321, 322].

Table 3: Economic parameters.

Parameter	Value
Oil price (USD/bbl)	70 (55 and 85 sensitivity)
Net revenue fraction after royalties and transport	0.75
Gas price (USD/Mscf)	2.5 (1.0 and 4.0 sensitivity)
Lifting cost (USD per bbl oil)	4.0
Water handling cost (USD per bbl water)	0.6
New compressor unit, gas engine and electric (USD million)	2.4 and 2.1
Conversion of existing units to electric (USD million each)	1.0
Grid connection for electric drives (USD million)	4.0
Flare gas recovery capital (USD million)	1.5 + 2.0 per MMscfd
Compressor fixed operating cost, engine and electric (USD million per unit-year)	0.12 and 0.07
Flare gas recovery operating cost (per year)	5 percent of capital
Power price (USD/MWh)	65
Carbon price (USD/t CO ₂ e)	0 (50, 100 and 150 sensitivity)
Discount rate	0.10

3.8. Optimization Problem and Solution

The Design Problem Is

$$\max_x \Delta NPV(x), \max_x Q_{oil}(x), \min_x E(x) \quad (10)$$

where $x = (n_{new}, d, P_s, C_F, L)$ collects the number of new units, the driver type, the suction pressure, the flare gas recovery capacity and the lift gas rate within the bounds in Table 4. Integer variables were handled by rounding within a

real-coded NSGA-II, with suction pressure rounded to 5 psia and recovery capacity and lift gas to 0.25 MMscfd [225, 226, 243]. NSGA-II was run with a population of 120 for 200 generations. Because the problem has only five variables, its Pareto front was also obtained by exhaustive enumeration of 29,250 designs on a grid of 5 unit counts, 2 driver types, 15 suction pressures, 13 recovery capacities and 15 lift gas rates, and the two fronts were compared by the hypervolume indicator computed on normalized objectives [237–239]. The final front was the non-dominated union of both sets.

Table 4: Decision variables and bounds.

Variable	Symbol	Range	Resolution
New compressor units	n_{new}	0 to 4	Integer
Driver type	d	Gas engine or electric	Binary
Suction pressure (psia)	P_s	40 to 250	5 (NSGA-II); 15 (grid)
Flare gas recovery capacity (MMscfd)	C_F	0 to 3	0.25
Total lift gas (MMscfd)	L	0 to 14	0.25 (NSGA-II); 1 (grid)

Representative designs were selected from the part of the front with non-negative incremental net present value, because designs that destroy value would not be adopted however low their emissions. The maximum-value design, the compromise design chosen by TOPSIS with equal weights on the three normalized objectives [240–242] and the lowest-emission design with non-negative value gain were compared with the current operation.

3.9. Lever, Scenario and Uncertainty Analysis

The contribution of individual levers was measured by changing one variable at a time from the current operation: adding one unit, lowering suction pressure to 100 psia, raising lift gas to 8 MMscfd, installing 2.0 MMscfd of flare gas recovery and converting to electric drivers. For levers that reduce emissions, the abatement cost was computed as the loss of net present value divided by the cumulative emissions avoided [198, 199, 202]. Scenario analysis re-optimized the design for maximum net present value under carbon prices of USD 50, 100 and 150 per tonne, oil prices of USD 55 and 85 per barrel, gas prices of USD 1.0 and 4.0 per Mscf, a flare efficiency of 91 percent and a grid factor of 0.20 t per MWh [312, 314]. Uncertainty analysis evaluated the representative designs in 200 Monte Carlo samples in which the reservoir decline rate, gas-oil ratio growth, water cut growth, oil and gas prices, low-pressure flare flow, flare efficiency and grid factor were drawn from the ranges in Table 8, following the approach of uncertainty studies in oil field emissions and production optimization [255, 271, 292].

4. Results

This section reports the current operation, the Pareto front and its verification, the representative designs, the contributions of individual levers, the scenario results and the uncertainty analysis. All values are for the representative field and inputs described in Section 3 and are expressed as cumulative totals over the ten-year horizon unless stated

otherwise [1, 4, 292]. Comparisons between designs are more informative than absolute values, because all designs share the same reservoir, price and emissions assumptions, so differences between them reflect only the design choices. The subsections move from the current operation to the optimized designs and then test how robust those designs are.

4.1. Current Operation

Under the current operation, with the three existing gas engine units, a suction pressure of 150 psia, 5 MMscfd of lift gas and no flare gas recovery, the field produces 5,257 bbl/d of oil in the first year, declining to 2,478 bbl/d in the tenth year, for a cumulative 14.1 million barrels. The compressors draw 1.5 MW in the first year, well within the 2.2 MW installed, and flaring averages 1.4 MMscfd, of which 1.3 MMscfd is low-pressure header gas and the remainder gas displaced by compressor outages. The flaring intensity is 0.38 Mscf per barrel of oil. Cumulative emissions are 430 kt of carbon dioxide equivalent, of which flaring accounts for 82 percent, compressor drivers for 16 percent and venting for 2 percent, giving an emissions intensity of 20.4 kg per barrel of oil equivalent. This dominance of flaring in the upstream footprint is consistent with field-level studies of carbon intensity [4, 9, 203], and the intensity lies within the range reported for conventional United States production [4, 293].

4.2. Pareto Front and Verification

Figure 2 shows the Pareto front in the planes of emissions and incremental value and of emissions and oil. NSGA-II returned 120 non-dominated designs and the exhaustive search 234, and their union contained 236 non-dominated designs, of which 171 had non-negative incremental value. The hypervolume of the NSGA-II front was 0.979 and that of the exhaustive front 0.981 on normalized objectives, so NSGA-II recovered 99.8 percent of the attainable hypervolume, which agrees with benchmark results for NSGA-II on low-dimensional problems [52, 237, 238].

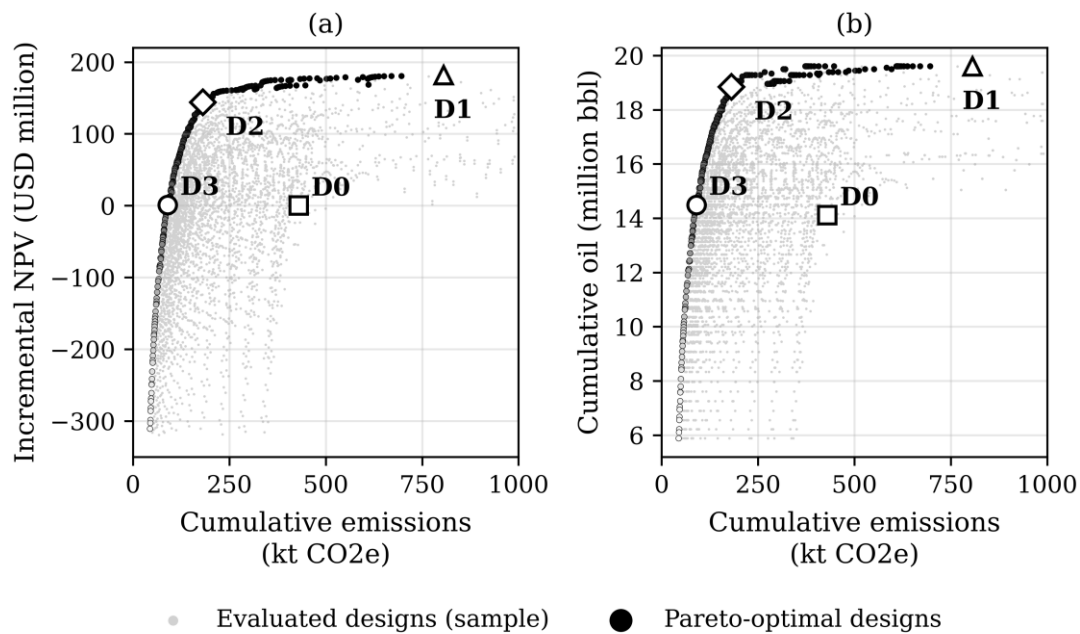


Fig 2: Pareto front of the three-objective problem: (a) incremental net present value against cumulative emissions and (b) cumulative oil against cumulative emissions. Grey points are a sample of all evaluated designs, and the marked points are the current operation (D0) and the representative designs D1 to D3.

The front has a pronounced knee. Starting from the lowest-emission designs, which shut in most lift gas and destroy value, incremental value rises steeply as emissions increase to about 180 kt, and then flattens: the last 38 million US dollars of value gain cost about 625 kt of additional emissions. The same pattern holds for oil production, which rises from 14.5 to 18.9 million barrels between 90 and 180 kt and then by only 0.7 million barrels as emissions rise to 806 kt. This shape implies that most of the value of compression

and lift gas expansion can be captured at a small fraction of the emissions of the value-maximizing design, which is the central result of the study [49, 242, 244].

4.3. Representative Designs

Table 5 compares the current operation (D0) with the three representative designs, and Figure 3 shows their annual profiles.

Table 5: Decision variables and performance of the current operation and the representative designs over the ten-year horizon.

Item	D0 Current	D1 Maximum value	D2 Compromise	D3 Minimum emissions
New compressor units	0	4	4	1
Driver type	Engine	Engine	Electric	Electric
Suction pressure (psia)	150	40	75	220
Flare gas recovery (MMscfd)	0	0	3.0	3.0
Lift gas (MMscfd)	5	14	14	9
Capital cost (USD million)	0	9.6	22.9	16.6
Incremental NPV (USD million)	0	181.7	144.0	1.1
Cumulative oil (million bbl)	14.1	19.6	18.9	14.5
Cumulative flared gas (Bcf)	5.31	8.60	0.46	0.38
Cumulative emissions (kt CO ₂ e)	430	806	181	90
Emissions intensity (kg CO ₂ e/boe)	20.4	28.3	6.2	4.0
Energy intensity (kWh/boe)	6.4	14.6	12.1	6.4

The maximum-value design D1 adds four engine-driven units, lowers suction pressure to 40 psia and raises lift gas to the 14 MMscfd limit. Oil production rises by 39 percent to 19.6 million barrels and incremental value is USD 182 million, but emissions almost double to 806 kt, because the lower suction pressure and larger lift gas volume raise compression power from 1.5 to 4.7 MW and engine fuel use

with it, and because more gas is flared during compressor outages and no low-pressure gas is recovered. Flaring rises to 2.3 MMscfd in the first year. Its emissions intensity of 28.3 kg per barrel of oil equivalent is 39 percent above the current operation, illustrating how production-maximizing operation of a mature field can increase both absolute emissions and intensity, as field age studies predict [1, 3, 4].

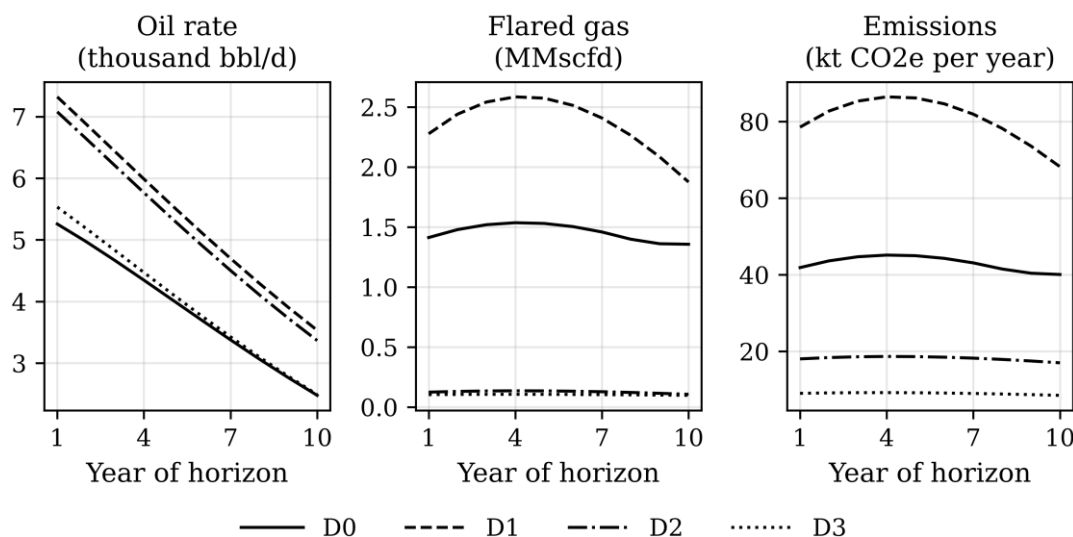


Fig 3: Annual oil rate, flared gas and emissions for the current operation (D0) and the representative designs D1 to D3.

The compromise design D2 uses the same four new units and the same lift gas, but with electric drivers, a suction pressure of 75 psia and 3.0 MMscfd of flare gas recovery. It retains 79 percent of the value gain of D1 (USD 144 million) and 86 percent of its oil gain, producing 18.9 million barrels, while reducing emissions by 58 percent relative to the current operation and by 78 percent relative to D1. Flaring falls by 91 percent to 0.46 Bcf over ten years, and the emissions intensity falls to 6.2 kg per barrel of oil equivalent. The difference in value between D1 and D2 is due mainly to the USD 13 million of additional capital for electrification and flare gas recovery and the cost of grid power, partly offset by sales of recovered gas and by the lower maintenance cost of electric drives [31, 33, 44].

The minimum-emission design D3 with non-negative value gain keeps production close to the current level, with one new electric unit, a suction pressure of 220 psia, 9 MMscfd of lift

gas and 3.0 MMscfd of recovery. It reduces emissions by 79 percent to 90 kt at zero net cost, which shows that large emission reductions are available without sacrificing value even if production is not increased. Compared with D3, D2 doubles emissions but adds 4.4 million barrels and USD 143 million, an implied trade-off of about 21 kg of carbon dioxide equivalent per incremental barrel, which is well below the average intensity of the current operation [4, 293].

4.4. Emission Sources and Individual Levers

Figure 4 shows the emissions of each design by source and the effect of individual levers, and Table 6 reports the lever results. Flaring dominates the current operation and the maximum-value design, while compressor drivers dominate the compromise and minimum-emission designs, in which flaring is almost eliminated and remaining emissions come from grid power and venting.

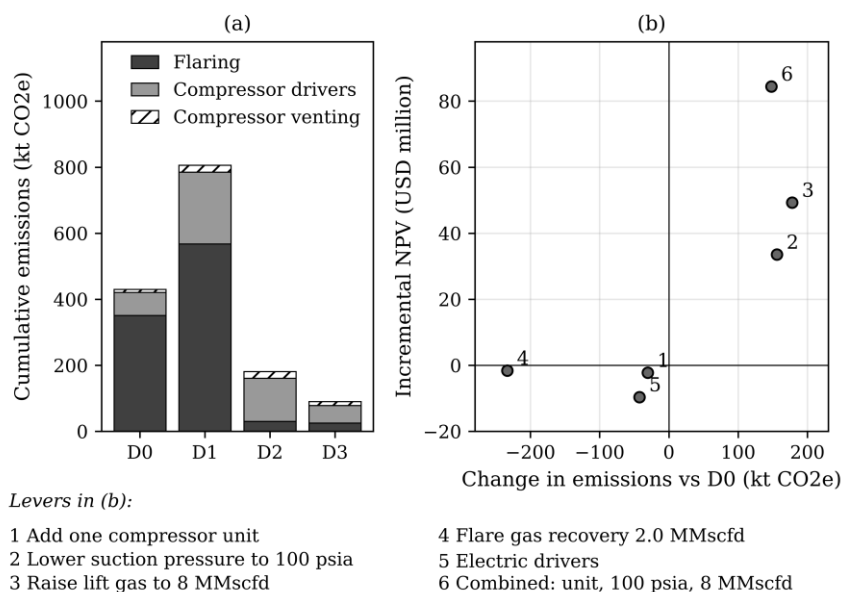


Fig 4: (a) Cumulative emissions by source for the current operation and the representative designs and (b) change in incremental net present value and emissions for individual levers applied to the current operation.

Table 6: Effect of individual levers applied to the current operation over the ten-year horizon.

Lever	Incremental NPV (USD million)	Cumulative oil (million bbl)	Cumulative emissions (kt CO ₂ e)	Abatement cost (USD/t CO ₂ e)
Add one compressor unit	-2.3	14.1	399	74
Lower suction pressure to 100 psia	33.5	15.1	586	Not applicable
Raise lift gas to 8 MMscfd	49.3	15.5	608	Not applicable
Flare gas recovery, 2.0 MMscfd	-1.6	14.1	196	7
Electric drivers	-9.6	14.1	387	226
One unit, 100 psia and 8 MMscfd combined	84.5	16.6	578	Not applicable

The production levers, lower suction pressure and more lift gas, each add USD 34 to 49 million in value and 1.0 to 1.4 million barrels, but each raises emissions by 36 to 41 percent, because the existing compression is then close to capacity and more gas is flared during outages and burned as engine fuel. Combining them with an extra unit increases value by USD 84 million, more than the sum of the separate levers, because the extra unit relieves the capacity constraint that limits each lever on its own. This interaction is the reason that compression capacity, suction pressure and lift gas must be optimized together [27, 166, 167].

Flare gas recovery is by far the cheapest abatement lever. A 2.0 MMscfd system reduces cumulative emissions by 233 kt, or 54 percent, at a net cost of USD 1.6 million, an abatement cost of about USD 7 per tonne, because the recovered gas is sold. This is consistent with the favourable economics reported for recovery systems in other settings [31, 32, 183]. Adding a compressor unit alone reduces outage flaring at USD 74 per tonne, while converting the existing station to

electric drives reduces emissions by 43 kt at USD 226 per tonne, because the conversion and grid connection costs are high relative to the driver emissions avoided at a grid factor of 0.37 t per MWh [33–35].

4.5. Scenario Analysis

Table 7 and Figure 5 show the value-maximizing design under alternative prices and assumptions. Under the reference assumptions, the value-maximizing design installs no flare gas recovery, because the gas price of USD 2.5 per Mscf barely covers the cost of recovery. A carbon price of USD 50 per tonne changes this: the value-maximizing design then installs 1.5 MMscfd of recovery and raises suction pressure slightly to 55 psia, which cuts emissions from 806 to 368 kt, below the current operation, while sacrificing only 0.3 million barrels. At USD 100 and 150 per tonne the recovery capacity rises to 2.0 MMscfd and emissions fall to 350 kt. Electrification was not selected in any scenario, because its abatement cost exceeds the carbon prices tested.

Table 7: Value-maximizing design under alternative scenarios. In every scenario the design used four new engine-driven units and 14 MMscfd of lift gas.

Scenario	Suction pressure (psia)	Recovery (MMscfd)	Incremental NPV (USD million)	Oil (million bbl)	Emissions (kt CO ₂ e)
Reference	40	0.0	181.7	19.6	806
Carbon price USD 50/t	55	1.5	176.8	19.3	368
Carbon price USD 100/t	55	2.0	179.1	19.3	350
Carbon price USD 150/t	55	2.0	181.6	19.3	350
Oil price USD 55/bbl	40	0.0	139.6	19.6	806
Oil price USD 85/bbl	40	0.0	223.9	19.6	806
Gas price USD 1.0/Mscf	40	0.0	170.6	19.6	806
Gas price USD 4.0/Mscf	40	1.25	193.7	19.6	651
Flare efficiency 91 percent	40	0.0	181.7	19.6	1,047
Grid factor 0.20 t/MWh	40	0.0	181.7	19.6	806

In the carbon price scenarios, incremental net present value is measured against the current operation under the same carbon price, so it includes the carbon cost avoided relative

to that operation, the convention used in studies of carbon taxes in oil production [312, 314].

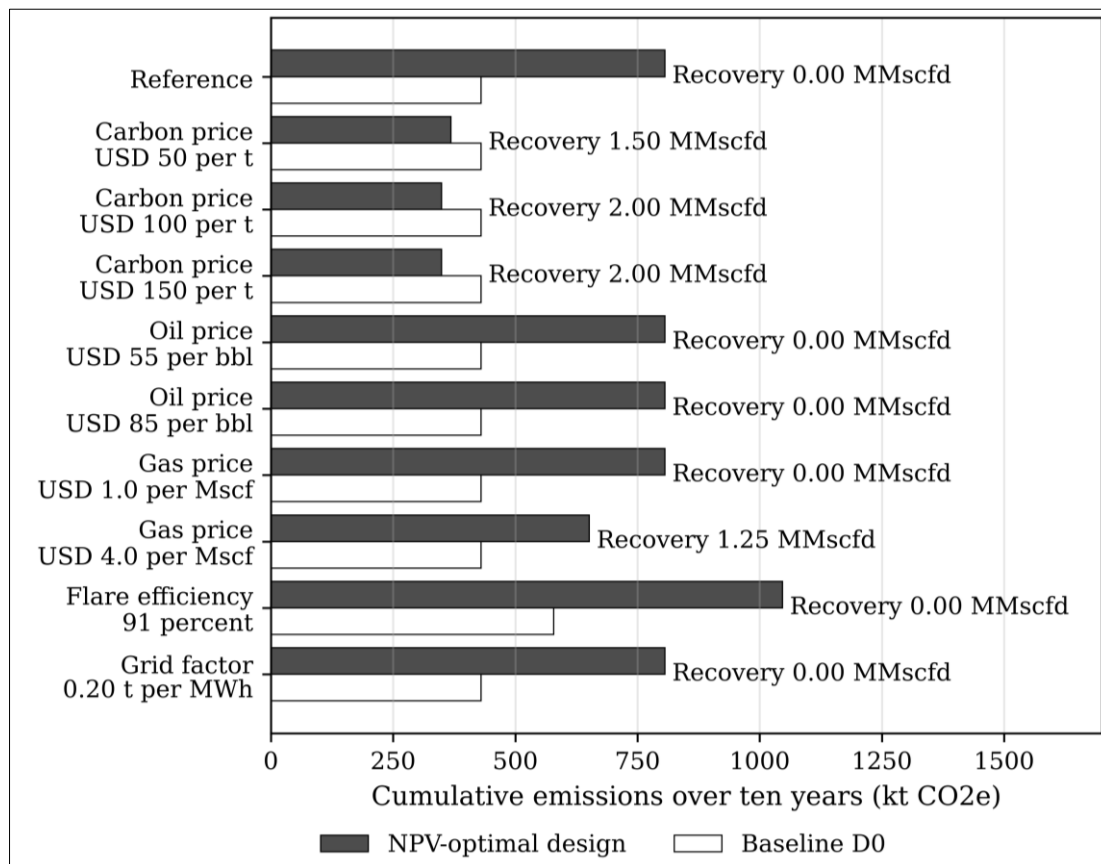


Fig 5: Cumulative emissions of the value-maximizing design and of the current operation under each scenario, with the flare gas recovery capacity selected.

Oil price changes alter the value of the maximum-value design by USD 42 million in each direction but do not change the design, because the production levers remain profitable over the range tested. A gas price of USD 4.0 per Mscf makes 1.25 MMscfd of recovery profitable without a carbon price, reducing emissions by 19 percent, while a gas price of USD 1.0 per Mscf, as experienced at the Waha hub during takeaway constraints, removes any private incentive to recover gas^[8, 313]. If flare combustion efficiency is 91 percent rather than 98 percent, as some field measurements suggest^[14, 16, 17], emissions of the value-maximizing design rise by 30

percent to 1,047 kt and those of the current operation by 35 percent to 578 kt, which makes flaring reduction even more important. A cleaner grid lowers the emissions of electric designs but does not by itself change the value-maximizing design, because there is no carbon price in that scenario.

4.6. Uncertainty Analysis

Table 8 summarizes the ranges sampled, and Figure 6 and Table 9 show the distribution of outcomes for the representative designs relative to the current operation evaluated under the same sample.

Table 8: Parameter ranges used in the Monte Carlo analysis.

Parameter	Distribution
Reservoir pressure decline rate (per year)	Uniform 0.012 to 0.026
Gas-oil ratio growth (per year)	Uniform 0.05 to 0.15
Water cut increase (per year)	Uniform 0.008 to 0.018
Oil price (USD/bbl)	Triangular 50, 70, 90
Gas price (USD/Mscf)	Triangular 0.5, 2.5, 4.5
Mean low-pressure flare flow (MMscfd)	Uniform 0.9 to 1.7
Flare combustion efficiency	Uniform 0.90 to 0.99
Grid emission factor (t CO2/MWh)	Uniform 0.25 to 0.45

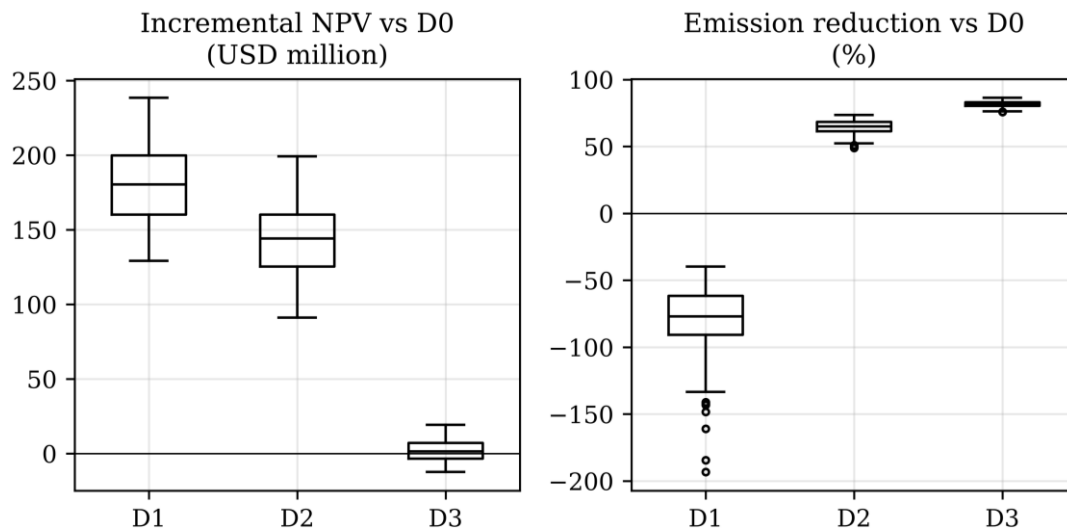


Fig 6: Distribution of incremental net present value and emission reduction relative to the current operation for the representative designs across 200 Monte Carlo samples; negative reductions indicate higher emissions than the current operation.

Table 9: Outcomes of the representative designs relative to the current operation across 200 Monte Carlo samples (5th percentile, median and 95th percentile).

Design	Incremental NPV (USD million)	Probability of positive incremental NPV	Emission change (percent)	Oil change (percent)
D1 Maximum value	135, 180, 217	1.00	+49, +77, +125	+35, +40, +47
D2 Compromise	99, 144, 181	1.00	-55, -65, -72	+29, +35, +41
D3 Minimum emissions	-9, 2, 15	0.59	-78, -82, -85	+0.4, +3.1, +6.0

The ranking of the designs was stable. The compromise design D2 had positive incremental value in every sample, with a median of USD 144 million and a 90 percent interval of USD 99 to 181 million, and it reduced emissions in every sample, by 49 to 73 percent, with a median of 65 percent. Its value gain was a median of 80 percent of that of D1 in the same sample, with a 90 percent interval of 73 to 85 percent, which confirms that the knee of the front is a structural feature rather than an artefact of the reference inputs. The maximum-value design D1 increased emissions in every sample, by 40 to 193 percent, and its emissions penalty was largest when flare efficiency was low and gas-oil ratio growth high. The minimum-emission design D3 always cut emissions by more than three quarters, but its value gain was close to zero and positive in only 59 percent of samples, so it is economically fragile, being sensitive mainly to the gas price that determines the value of recovered gas [255, 271, 292]. The median emission reduction of D2 under uncertainty (65 percent) is larger than in the reference case (58 percent) because lower flare efficiencies in the sampled range increase the emissions of the current operation more than those of D2, in which little gas is flared [14, 16].

5. Discussion

This section interprets the findings, draws implications for operators and for policy, and sets out the limitations of the study. The discussion is framed by two observations from the literature: that the carbon intensity of oil production rises with field age [1, 2] and that flaring and venting are among the largest and most controllable sources of upstream emissions [4, 8, 9]. It also considers how the results relate to the wider practice of integrated production optimization and to the measurement of flare and compressor emissions on which any such optimization depends [16, 166, 214]. The emphasis is on

what the results imply for decisions rather than on their absolute values.

5.1. Principal Findings

Three findings stand out. First, maximizing value alone in a mature gas-lifted field is likely to increase emissions substantially. The levers that raise production, lower suction pressure, more lift gas and more compression, all increase compression power and, with engine drivers and limited recovery capacity, increase fuel use and flaring. In the representative field, the value-maximizing design raised oil production by 39 percent but nearly doubled cumulative emissions and raised their intensity by 39 percent. This is the mechanism behind the observation that older fields are more emissions-intensive [1, 3, 5], and it implies that production enhancement projects in mature fields should be evaluated jointly with their emissions consequences [4, 286].

Second, the trade-off between value and emissions is highly non-linear. The Pareto front has a pronounced knee: a compromise design kept 79 percent of the maximum value gain and 86 percent of the oil gain while reducing emissions by 58 percent relative to the current operation. The knee arises because flare gas recovery and electrification remove most of the emissions associated with the production levers at a small fraction of their value. Similar knees have been reported in multi-objective studies of gas networks and production systems [50, 51, 244], and they are what makes multi-objective analysis useful to decision makers: a single-objective optimum on either side of the knee would miss most of the attainable value or most of the attainable emission reduction [240–242].

Third, the abatement levers differ greatly in cost. Flare gas recovery cost about USD 7 per tonne because recovered gas has value, adding compression to reduce outage flaring cost

about USD 74 per tonne and electrification about USD 226 per tonne at the assumed grid factor; the cost of electrification would fall as grid architectures accommodate more renewable generation and distributed resources ^[320, 323]. This ranking is consistent with marginal abatement studies that place flaring and venting reduction among the cheapest upstream options ^[198, 199, 202], and with the experience that electrification is most attractive where grid power is clean and inexpensive or where it is combined with other benefits such as higher availability and lower maintenance ^[33–35]. The scenario results show that a modest carbon price of USD 50 per tonne is sufficient to make flare gas recovery part of the value-maximizing design and to bring emissions below the current level while keeping almost all of the production gain.

5.2. Implications for Operators

For operators of mature fields, the results suggest a sequence of actions. The first is to treat compression capacity, suction pressure, lift gas and flare gas recovery as a single design problem, because the levers interact through shared compression capacity; in the representative field, adding a unit together with lower suction pressure and more lift gas created more value than the sum of the separate levers ^[164, 166, 167]. The second is to install flare gas recovery sized for the bulk of the low-pressure header flow rather than its peaks, because the long tail of the flow distribution makes the last increments of capacity expensive; in the model, 2.0 MMscfd of capacity recovered 87 percent of the mean flow of 1.3 MMscfd ^[30, 31, 44]. The third is to evaluate electrification as part of a compression expansion rather than as a stand-alone retrofit, because the incremental cost of electric drivers is lowest when new units are being installed and because electric motors improve availability ^[33, 35, 103]. The fourth is to measure flare combustion efficiency and low-pressure header flows, because both strongly affect the benefit of recovery and are poorly known in many facilities ^[14, 17, 210].

Reliability engineering supports these actions. Condition monitoring and fault diagnosis of reciprocating compressor valves and packing reduce unplanned outages and the flaring they cause ^[87, 89, 92], and real-time optimization of load sharing and lift gas allocation keeps the system close to its optimum as conditions change ^[42, 61, 147]. Digital integrated field management programmes and closed-loop production optimization provide the data and workflows needed to implement such optimization in practice ^[144, 168, 263], and surrogate and machine learning models of well and compressor performance can make multi-objective optimization fast enough for operational use ^[81, 83, 249]. Tiered digital twins have shown how predictive diagnostics can be brought to sites with limited instrumentation and computing resources ^[324], and condition-based maintenance of offshore export equipment ^[325] and non-intrusive inspection of pressure vessels ^[326, 327] reduce the shutdowns that force gas to the flare. Corrosion management and material selection ^[328], integrity management of fired equipment ^[329] and occupational safety risk control during construction ^[330] matter when new compressor units and recovery systems are added to an ageing facility, and a resilient supply chain for critical spares supports the availability assumed in the model ^[331].

5.3. Implications for Policy and Regulation

The scenario analysis has two implications for policy. First, carbon pricing is effective at the low-cost end of the

abatement curve: a price of USD 50 per tonne changed the value-maximizing design to include flare gas recovery and halved its emissions, while the incremental value of that design fell by less than 3 percent. Carbon taxes have influenced upstream emissions in Norway in this way ^[311], and the International Energy Agency has described how carbon costs and emission commitments are changing investment in the oil and gas industry ^[315], while greenhouse gas disclosure and ESG compliance obligations increase the scrutiny of flaring by investors and regulators ^[316]. Second, low gas prices caused by takeaway constraints undermine the private case for recovery, so policies that address gas takeaway, such as pipeline access and gas capture requirements, complement carbon pricing ^[7, 8, 313]. Regulatory design matters, since inefficient flaring rules can raise costs without proportionate benefit, as evidence from the Bakken in North Dakota shows ^[313]. Studies of carbon taxes in production optimization ^[312, 314] and of carbon dioxide enhanced oil recovery ^[303–305] show that the interaction between emissions costs and production decisions extends beyond flaring.

5.4. Limitations

The study has several limitations. All parameters are representative values rather than data from a specific field, so absolute results should not be transferred without calibration against well tests, compressor performance data and measured flare volumes ^[285, 291, 292]. The well model uses a linear inflow relationship and a simplified gradient correlation rather than a full multiphase flow model, and the reservoir is represented by exponential decline rather than simulation ^[169, 170, 265]. Design variables were held constant over the ten years, whereas in practice lift gas and suction pressure would be adjusted as the field declines, and staged investment could improve value ^[48, 262, 267]. Compressor availability was treated as independent between units and constant over time, without common-cause failures or degradation ^[87, 101]. Emissions accounting excluded fugitive emissions from wells and equipment other than compressors, tank venting not routed to the flare and emissions embodied in equipment ^[221, 222, 287]. The analysis did not include the time value of methane or near-term warming metrics, which would increase the weight on methane slip from flares and engines ^[10, 11]. Finally, the uncertainty analysis covered reservoir, price and emissions parameters but not structural uncertainty in the models themselves ^[255, 271, 272].

6. Conclusion

This study developed a multi-objective framework for the joint design of gas compression, flare gas recovery and production in mature gas-lifted oil fields, coupling well inflow and gas-lift performance, multistage compression, compressor availability, flare header flow variability, emissions accounting and discounted cash flow, and solving the three-objective problem in value, oil production and emissions with NSGA-II verified against exhaustive search. In the representative field, maximizing value alone raised oil production by 39 percent but nearly doubled emissions, because the levers that increase production also increase compression power, engine fuel use and flaring. The Pareto front had a pronounced knee, and a compromise design with four electric-driven units, a moderately reduced suction pressure, full lift gas and 3 MMscfd of flare gas recovery kept most of the value and production gain while cutting emissions

by more than half and flaring by more than 90 percent. Flare gas recovery was the cheapest abatement lever, and a modest carbon price was enough to make it part of the value-maximizing design. The compromise design remained valuable and lower in emissions than the current operation across the range of reservoir, price and emissions uncertainty tested.

For operators of mature fields, the results support treating compression, suction pressure, lift gas and flare recovery as one design problem, sizing recovery for the bulk of low-pressure flow, combining electrification with compression expansion and measuring flare efficiency and header flows. Further work should calibrate the framework with field data, allow staged and time-varying decisions and extend the emissions accounting to all upstream sources.

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