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# Multi Objective Optimization of Farm Energy and Water Consumption in Solar Powered Agriculture

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**Abstract** – While solar photovoltaic (PV) pumping reduces the cost and carbon footprint of irrigating, the sizing of the PV array, storage tank, and irrigation schedule are ignoring the groundwater that is pumped and the yield at risk. This paper presents the design and operation of a grid-connected, solar-powered, drip-irrigated farm as a three-objective optimisation problem with the aim of minimising the net annual cost (including the revenue loss due to yield deficit), the grid electricity import and water withdrawal, subject to a minimum relative yield of 85 %. The decision variables are PV capacity, battery capacity, water-tank volume, the irrigation ratio (the proportion of crop water requirement applied) and the percentage of irrigation moved to the solar window. The energy-water dispatch model is implemented per hour; the soil-water and yield-response model is implemented per day and is based on the FAO-56 model; an elitist non-dominated sorting genetic algorithm (NSGA-II) with external archive is used to solve the problem. The hypervolume for the archive-based NSGA-II was hypervolume = 0.982, whereas the hypervolume for random search was hypervolume = 0.963 (after running 6480 simulations). The minimum cost design reduced grid import by 79 % and net annual cost by 27 % compared to a grid-powered farm with full irrigation, whereas a balanced design, keeping the yield at or above 95 %, saved 21 % of water and 99 % of grid energy. The cheapest lever was to shift irrigation to the solar window and the tank was used as a battery storage. The best designs were still possible in dry and wet years, while crop price and PV cost were most sensitive to the cost. The Pareto set provides a clear picture to growers and planners of the energy/water/money trade-offs.

**Keywords** – Solar Irrigation, Water–Energy Nexus, Multi-Objective Optimisation, NSGA-II, Deficit Irrigation, Photovoltaic Pumping, Precision Agriculture.

## I. INTRODUCTION AND RELATED WORK

Irrigation agriculture is based on two interdependent and increasingly limited resources – water, accessed through wells, canals, and water storage tanks, and energy, for lifting, transporting, and pressurising water. Groundwater pumping can be a significant portion of the electricity used on farms in many parts of agriculture. Consumption of subsidised electricity, intermittent electrical power supply and diesel pumping cause economic, operational and environmental problems. Solar PV pumping has thus become a promising approach to enhance the energy sustainability of irrigation systems. The technically related reviews have already considered the PV pumping configurations, the selection of the components, the sizing of the PV system, and its applications in agricultural irrigation and community water supply [1]. Preliminary field trials in arid areas have also shown the feasibility of small-scale PV pumping for reliable irrigation and decrease

dependence on traditional fuels [2]. But the applicability of solar-powered irrigation relies more on the coordination of energy availability, water demand, storage capacity, and crop requirements, than on the electricity generation.

Most of the research has been geared towards reducing or optimizing either energy consumption, installation expenses, or life-cycle operating costs. Economic optimisation techniques have been considered to determine the optimal PV array size and energy-storage size for irrigation purposes [3]. Comparative studies of grid connected, stand-alone solar-powered and conventional irrigation systems have also provided potential economic and environmental advantages, depending upon system configuration, grid electricity costs, climatic conditions and the availability of grid electricity [4]. Despite such contributions, irrigation demand has been often considered as an input of the irrigation system, rather than as a design and operational parameter. This is because the assumption restricts the opportunities for finding configurations that can simultaneously lower the investment costs, electricity imports and groundwater extraction. The amount of irrigation needed will depend on the amount of rainfall received, evapotranspiration, crop growth stages, soil characteristics as well as water availability. Thus, by integrating the irrigation scheduling into the optimisation framework, the coordination of energy supply and agricultural water management can be improved.

Deficit irrigation is one that can offer a significant solution to this constraint. Under this strategy, the amount of water provided is intentionally limited during specific time periods to below an estimated full crop-water requirement. However, water use and pumping needs can be reduced and crop productivity remain acceptable with appropriate deficit irrigation, but the yield response will vary with the sensitivity of the crop, the stage of crop development, soil-water availability and climatic conditions [5]. So, water productivity and water-use indicators have been recommended and suggested as tools to estimate irrigation efficiency and agricultural resource utilisation [6]. Moreover, crop water-footprint analysis has demonstrated that irrigation is the significant part of all agricultural water use, especially in water-scarce areas [7]. These results suggest that a design optimization for energy requirements can yield economically viable designs at the expense of too much ground water stress. By the same token, if water is withdrawn to the absolute minimum, without taking into account the crop response and the economic returns, then unacceptable yield reductions or increased production costs could result. These conflicting effects, therefore, need to be quantified in an integrated optimisation framework.

The simultaneous optimization of economic costs, grid electricity import and groundwater withdrawal is a multi-objective optimization problem. The objectives may be contradictory, as increasing PV generation or battery storage may be needed to reduce grid dependence, while changing the irrigation schedule may impact crop yield and revenue, and thus water use. However, a single criterion may mask such trade-offs since the optimal solutions will be different depending on the values of the weighting coefficients. Multi-objective evolutionary algorithms overcome this limitation by producing a set of non-dominated solutions that are usually displayed on a so-called Pareto front. The solutions are configurations that each imply a decrease in at least one objective in relation to the improvement made in another objective [8]. The NSGA-II is an elitist non-dominated sorting genetic algorithm (GA) that has been successfully used for engineering optimisation tasks due to its non-dominated sorting, crowding-distance operator and ability to maintain high-quality candidate solutions from generation to generation [9]. An external archive will also be able to store non-dominated solutions found during the search process.

Optimisation of solar powered agricultural systems is a particularly difficult task due to three technical issues that are interlinked. First, irrigation schedules can be adjusted to match high sun energy production. This temporal flexibility can be used to enhance direct PV utilisation and minimise electricity imports from the grid, which may lead to a decrease in battery storage needs. Second, water tanks offer an indirect way to store the solar energy by pumping water while it was being generated, and then pumping it out to use for irrigation when it was needed. While this can cut down the use of electrochemical storage, the size of the tanks will need to be taken into consideration when considering water consumption, storage space and evaporation. Thirdly, irrigation deficits affect pumping needs and productivity of the crops. The economic value of the saved water therefore needs to be weighed against any yield losses and resulting crop income.

This study tackles these interactions with a three-objective optimisation approach for a grid connected, solar powered, drip irrigated farm. Decision variables are PV capacity, battery capacity, water-tank volume, irrigation ratio, and the proportion of irrigation time during the solar-generation time period. Applications of energy-dispatch model on hourly time scale are coupled with a daily FAO-56 soil-water balance and crop-yield response model to simulate the interactions between electricity supply, irrigation demand and agricultural productivity. Optimisation objectives include minimising the net annual cost, minimising grid electricity import, and minimising groundwater withdrawal, all with a minimum relative yield of 85%. The identification of non-dominated configurations and characterisation of the trade-offs between the three objectives is done using archive-based NSGA-II.

The main contribution is the simultaneous optimization of the energy system size, water storage, irrigation scheduling and deficit irrigation, in one common optimization framework. The resulting Pareto set enables selection of configurations based on their economic priorities, independence to the grid, or water conservation without using a single aggregated performance score. Comparative evaluation with random search combined with climate change robustness assessment serves as a basis for optimisation performance and the feasibility of candidate designs. The approach as a result thus provides a systematic way of assessing the potential for resource-efficient sun-powered farming, taking into consideration the conflicting demands for cost competitiveness, water management and crop yields.

The main contribution of the paper is that it provides a coupled hourly energy–water and daily crop-water model of a grid-connected solar farm, a three-objective formulation with the revenue lost to yield deficit and a minimum yield

constraint, a solution set using NSGA-II based on an archive and a comparison with random search, an analysis of the scheduling–storage–deficit irrigation trade-off along the Pareto front and selection of knee designs and balanced designs, and tests of the robustness of the selected designs to dry and wet years and to cost parameters.

## II. SYSTEM DESCRIPTION AND MODELLING

*Farm System*

The study system (**Fig. 1**) is a 5-ha drip-irrigated tomato farm with two crops per year in a tropical climate similar to that of western Tamil Nadu (latitude 11° N). A PV array feeds the farm bus through a hybrid inverter; a lithium battery, the grid connection, an on-farm pack-house and cold store, and a well pump with variable-frequency drive share the same bus. The pump lifts water from a borewell to an optional water tank, from which the drip field is supplied. The grid supplies any shortfall and accepts surplus PV energy at a lower export tariff. The pump serves the field either directly or through the tank, which acts as a low-cost store of water and therefore of energy.

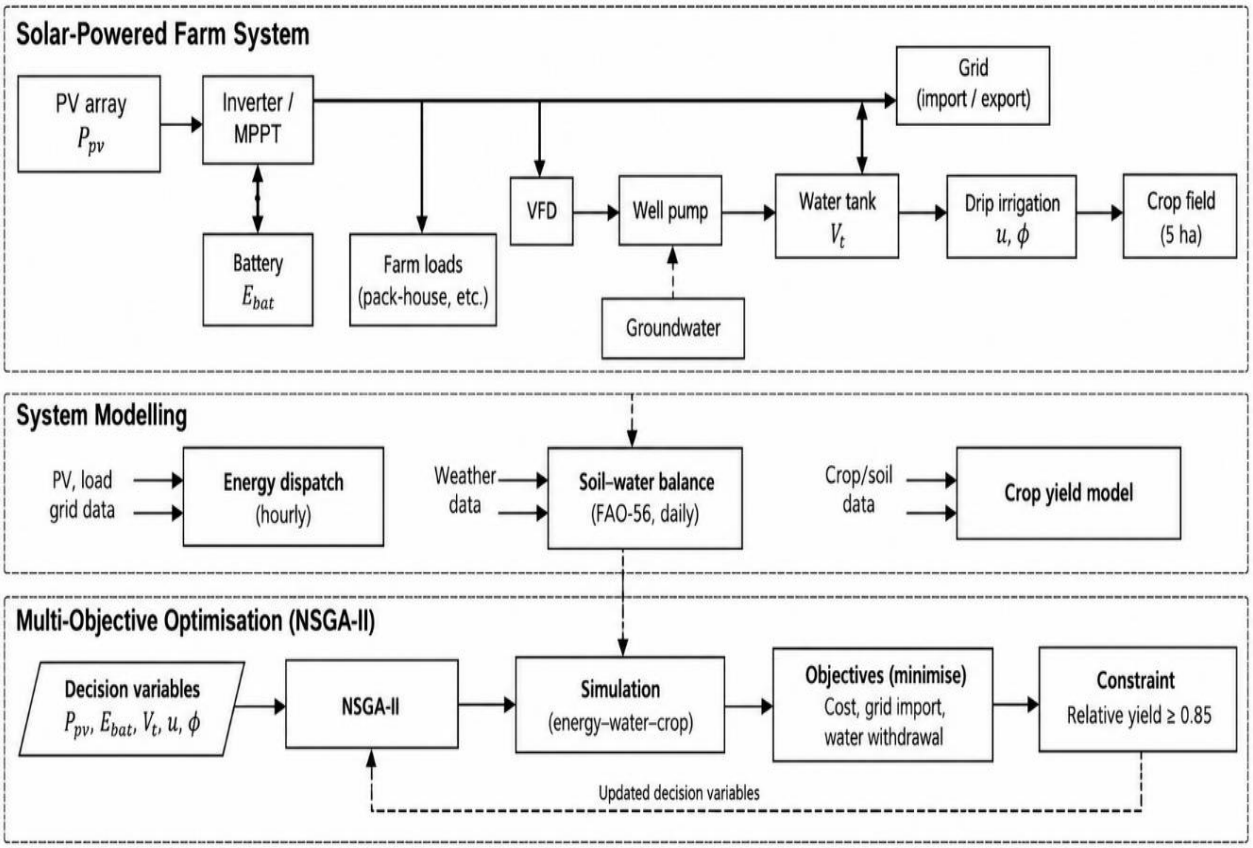



**Fig 1.** Grid-Connected Solar-Powered Farm System with the Decision Variables and Objectives of the Optimisation.

*Weather and Crop-Water Model*

A synthetic but climatologically realistic year was generated for the site (**Fig. 3**): annual global horizontal irradiation of 1.82 MWh m$^{-2}$ (4.97 kWh m$^{-2}$ d$^{-1}$), rainfall of 716 mm concentrated in the south-west and north-east monsoons, and reference evapotranspiration of 1695 mm. Daily extraterrestrial radiation and clearness indices were used to obtain daily radiation, which was distributed over the hours of the day by the Collares-Pereira and Rabl relationship [10]. Reference evapotranspiration was estimated with the Hargreaves equation [11] from mean temperature, temperature range and extraterrestrial radiation $R_a$:

$$\mathrm{ET_0} = 0.0023\mathrm{R_a}(\mathrm{T_{mean}} + 17.8)\sqrt{\mathrm{T_{max}} - \mathrm{T_{min}}} \quad (1)$$

Crop water use followed the FAO-56 single-crop-coefficient method [12]. The potential crop evapotranspiration is $ET_c = K_c\, ET_0$ with a four-stage coefficient (0.60 initial, rising to 1.15 at mid-season and falling to 0.80 at harvest) over two 120-day seasons (10 January and 15 August). The root-zone depletion $D_r$ evolves with effective rain $P_e$, applied net irrigation $I$ and actual evapotranspiration $ET_a$, which is reduced by the stress coefficient $K_s$ when depletion exceeds the readily available water ($p \cdot TAW$):

$$\mathrm{D_{r,i}} = \min\big(\max\big(\mathrm{D_{r,i-1}} - \mathrm{P_{e,i}} - \mathrm{I_i} + \mathrm{ET_{a,i}}, 0\big), \mathrm{TAW}\big), \quad \mathrm{K_s} = \frac{\mathrm{TAW} - \mathrm{D_r}}{(1-\mathrm{p})\mathrm{TAW}} \ \ (\text{for } \mathrm{D_r} > \mathrm{p} \cdot \mathrm{TAW}) \quad (2)$$

with $ET_a = K_s\,K_c\,ET_0$, $TAW$ = 70 mm and $p$ = 0.4. Irrigation is applied daily as a fraction $u$ of the net requirement not met by rain, the *irrigation ratio*, and the gross water volume follows from the application efficiency $E_a$ = 0.9 and the farm area $A$ (in ha; 1 mm over 1 ha is 10 m$^3$):

$$\mathrm{V_{irr}} = \frac{10\mathrm{A}\,\mathrm{u}\max(0,\mathrm{ET_c}-\mathrm{P_e})}{\mathrm{E_a}} \tag{3}$$

Yield was predicted with the linear yield-response function of FAO Irrigation and Drainage [13], with the seasonal yield-response factor $K_y$ = 1.05 for tomato:

$$1-\frac{\mathrm{Y_a}}{\mathrm{Y_m}} = \mathrm{K_y}\left(1-\frac{\sum_{\mathrm{season}}^{\mathrm{a}}\mathrm{ET_a}}{\sum_{\mathrm{season}}^{\mathrm{c}}\mathrm{ET_c}}\right) \tag{4}$$

The relative yield of the farm is the mean over the two seasons. The model is deliberately simple, to allow thousands of simulations; a process-based crop model such as AquaCrop [14] would represent canopy development and stress responses in greater detail and could replace it in a refined study.

*Energy and Water Dispatch Model*
The farm was simulated hourly over 8760 h. The power of the PV array of rated capacity $P_{pv}$ (kWp) is

$$\mathrm{P_{pv}(t)} = \mathrm{P_{pv}}\cdot\frac{\mathrm{G(t)}}{1\ \mathrm{kW\,m^{-2}}}\cdot\eta_{\mathrm{sys}}[1-\gamma(\mathrm{T_c}-25)],\quad \mathrm{T_c} = \mathrm{T_a} + \mathrm{k\,G} \tag{5}$$

where $G$ is the hourly irradiance, $\eta_{sys}$ = 0.82 the system efficiency, $\gamma$ = 0.004 K$^{-1}$ the temperature coefficient and $k$ = 30 K m$^2$ kW$^{-1}$. The electrical energy needed to lift one cubic metre of water through the total dynamic head $H$ (65 m) at wire-to-water efficiency $\eta_p$ (0.52) is

$$\mathrm{e_p} = \frac{\rho\,\mathrm{g\,H}}{3.6\times10^6\eta_{\mathrm{p}}} \approx 0.34\ \mathrm{kWh\ m^{-3}} \tag{6}$$

A booster pump adds 0.04 kWh m$^{-3}$ for delivery to the field. The irrigation volume of each hour is the daily volume distributed over two windows (06–09 h and 16–18 h) and a solar window (10–15 h); the fraction φ of daily volume placed in the solar window is a decision variable. Water is first taken from the tank; any shortfall is pumped directly. Surplus PV power, after meeting the farm load and direct pumping, refills the tank at a rate limited by the pump capacity (120 m$^3$ h$^{-1}$). The tank volume $L$ follows

$$\mathrm{L(t+1)} = \mathrm{L(t)} + \mathrm{q_{fill}(t)} - \mathrm{q_{draw}(t)} - \mathrm{q_{evap}(t)},\quad \mathrm{q_{evap}} = \frac{\mathrm{k_e ET_0}}{24}\frac{\mathrm{V_t}}{\mathrm{d_t}}\frac{\mathrm{L}}{\mathrm{V_t}} \tag{7}$$

where the evaporation loss is proportional to the water surface of an open tank of depth $d_t$ = 3 m, with pan coefficient $k_e$ = 1.1. The battery of capacity $E_b$ is limited to a state of charge between 20 % and 100 %, a power of 0.5$E_b$ per hour and a round-trip efficiency of about 90 %:

$$\mathrm{E_b(t+1)} = \mathrm{E_b(t)} + \eta_{\mathrm{c}}\mathrm{P_{ch}}\Delta\mathrm{t} - \frac{\mathrm{P_{dis}}\Delta\mathrm{t}}{\eta_{\mathrm{d}}} \tag{8}$$

Any remaining deficit is imported from the grid, and any remaining surplus is exported (or, equivalently, curtailed if the export tariff is zero), so that the power balance in each hour is

$$\mathrm{P_{pv}} + \mathrm{P_{dis}} + \mathrm{P_{imp}} = \mathrm{P_{load}} + \mathrm{P_{ch}} + \mathrm{P_{exp}} \tag{9}$$

with the load comprising the farm services (1.5 kW continuously and 3 kW more between 08 and 17 h), the pumping and the tank-filling energy. This rule-based dispatch is a transparent proxy for the dispatch that would be used in an energy management system; optimising the hourly dispatch together with the design would further improve the results.

*Optimisation Problem*
The annualised cost of the capital items is obtained with the capital recovery factor for discount rate $i$ and lifetime $n$,

$$\mathrm{CRF(i,n)} = \frac{\mathrm{i(1+i)^n}}{\mathrm{(1+i)^n-1}} \tag{10}$$

and the first objective, the net annual cost, adds the operating cost of grid energy and water, net of export revenue, and the opportunity cost of the yield deficit:

$$f_1 = \sum_k c_k x_k (\mathrm{CRF}(i, n_k) + o_k) + \tau_{imp} E_{imp} - \tau_{exp} E_{exp} + c_w W + p_y Y_m n A \left(1 - \frac{Y_a}{Y_m}\right) \quad (11)$$

where $k$ runs over PV, battery and tank, $c_k$ are unit costs, $o_k$ the O&M fraction, $\tau$ the import and export tariffs, $W$ the annual water withdrawal (irrigation plus tank evaporation), $c_w$ the water price, $p_y$ the crop price and $n = 2$ the number of seasons. The multi-objective problem is

$$\min \; F(x) = \left[f_1, E_{imp}, W\right], \quad \text{s.t.} \quad Y_a/Y_m \geq 0.85, \quad x_{lb} \leq x \leq x_{ub} \quad (12)$$

with $x = [P_{pv}, E_b, V_t, u, \varphi]$ and the bounds in **Table 2**. A design $x_1$ dominates $x_2$ if it is no worse in every objective and strictly better in at least one; the Pareto front is the set of non-dominated feasible designs. **Table 1** lists the main assumptions, which are indicative values for India and must be replaced by local prices.

**Table 1.** Main Model Assumptions (Indicative Values; to Be Replaced with Local Data)

| Parameter | Value | Parameter / value |
|---|---|---|
| PV installed cost | ₹45,000 per kWp | Battery cost: ₹14,000 per kWh (10-yr life) |
| Tank cost | ₹1,000 per m³ | Discount rate 8 %; PV and tank life 25 yr |
| Grid import tariff | ₹7.0 per kWh | Export tariff ₹2.5 per kWh |
| Water price | ₹1.5 per m³ | Tomato price ₹12,000 per t; $Y_m$ = 55 t ha$^{-1}$ per season |
| Total pumping head | 65 m | Wire-to-water efficiency 0.52 |
| Soil TAW / depletion fraction | 70 mm / 0.4 | Drip efficiency 0.9; $K_y$ = 1.05 |
| Farm area | 5 ha | Grid emission factor 0.71 kg $CO_2$ per kWh |

**Table 2.** Decision Variables and Bounds.

| Variable | Range | Meaning |
|---|---|---|
| PV capacity $P_{pv}$ | 0–80 kWp | Installed array rating |
| Battery capacity $E_b$ | 0–200 kWh | Usable 80 % of nominal energy |
| Tank volume $V_t$ | 0–1500 m³ | Open lined tank, 3 m deep |
| Irrigation ratio $u$ | 0.50–1.00 | Fraction of net crop water requirement applied |
| Solar schedule φ | 0–0.60 | Fraction of daily irrigation moved to 10–15 h (agronomic limit) |

*Solution Method*

The problem was solved with NSGA-II [9] (**Fig. 2**). In each generation, offspring are created by binary tournament selection on non-domination rank and crowding distance, simulated binary crossover [15] and polynomial mutation; parents and offspring are merged, and the next population is filled front by front, with the last front truncated by crowding distance, so that sparsely populated regions of the front are preferred. Infeasible designs are dominated by feasible ones through a penalty on the constraint violation. Because all 6,480 designs evaluated by the search carry information, an external archive of non-dominated feasible designs (limited to 300 by crowding distance) was kept, which is standard practice when the population is smaller than the useful front. The population was 80 and the number of generations 80. Each evaluation is a one-year hourly simulation of the whole population, and the full run took 31 s on a general-purpose processor. For benchmarking, random search with the same number of evaluations was used, and the quality of the approximate fronts was compared by the hypervolume *HV*, the volume of objective space dominated by the front and bounded by a reference point [16], estimated by Monte Carlo sampling in objective space normalised between the ideal point and the nadir point of the NSGA-II archive. From the Pareto set, the *knee* design was identified as the one with the smallest Euclidean distance to the ideal point in normalised space [17],

$$d_i = \sum_{m=1}^{3} \frac{f_{m,i+1} - f_{m,i-1}}{f_{m,max} - f_{m,min}} \quad (13)$$

$$\delta_i = \sqrt{\sum_{m=1}^{3} \left( \frac{f_{m,i} - f_m^*}{f_m^{nad} - f_m^*} \right)^2} \quad (14)$$

and a *balanced* design as the knee among the designs with relative yield of at least 95 %, which a grower is more likely to accept than a design that sacrifices 7 to 15 % of yield. The selected designs were compared with three conventional baselines: A, a grid-powered pump with full irrigation; B, 20 kWp of solar PV without storage and with full irrigation; and C, as B but with 60 % of the irrigation moved to the solar window.

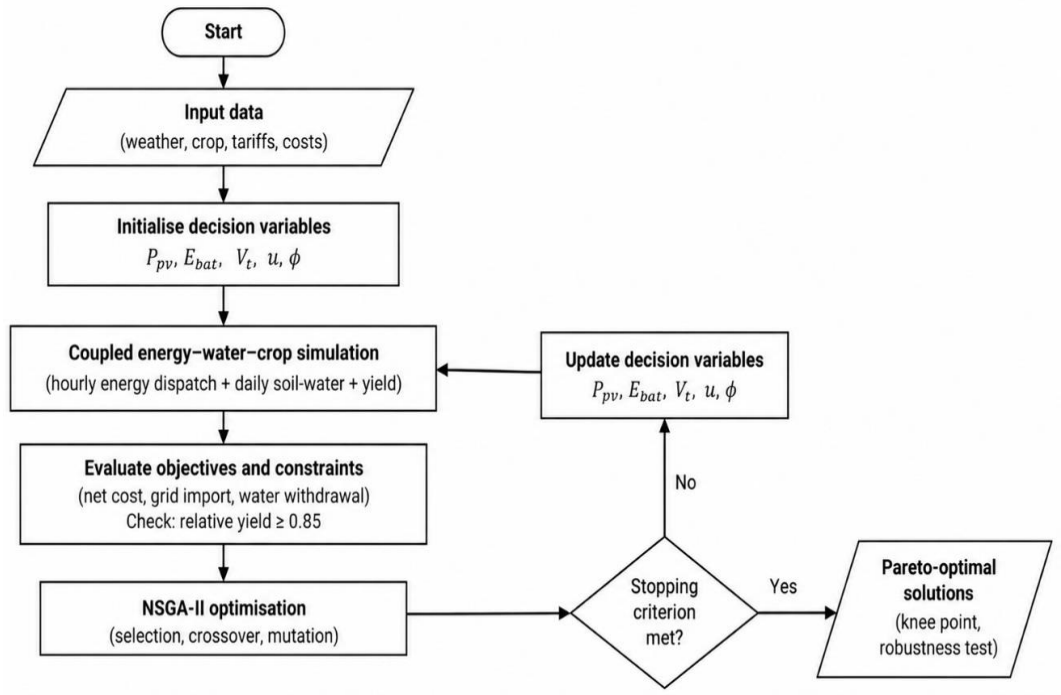



**Fig 2.** Workflow of the Optimisation Study.

## III. RESULTS AND DISCUSSION

*Weather, Crop Water Requirement and the Water–Yield Response*

**Fig. 3a** shows the water–yield response obtained by sweeping the irrigation ratio. Applying the full requirement ($u$ = 1) gave a relative yield of 1.00, but yield did not fall linearly from there. For ratios down to about 0.9, relative yield stayed near one, because the soil store and effective rain covered the shortfall, and below this it declined at a rate that depended strongly on the season. The first season (January–April), with only 69 mm of rain against a crop requirement of 546 mm, was much more sensitive to deficit than the second season, which received 561 mm during the north-east monsoon. The minimum irrigation consistent with 85 % yield was about 5.5 thousand m³ per hectare per year, compared with 9.5 thousand m³ at full irrigation, a saving of 42 %. This nonlinearity is why a moderate deficit is almost free in agronomic terms, whereas deeper deficits must be paid for in yield and income.

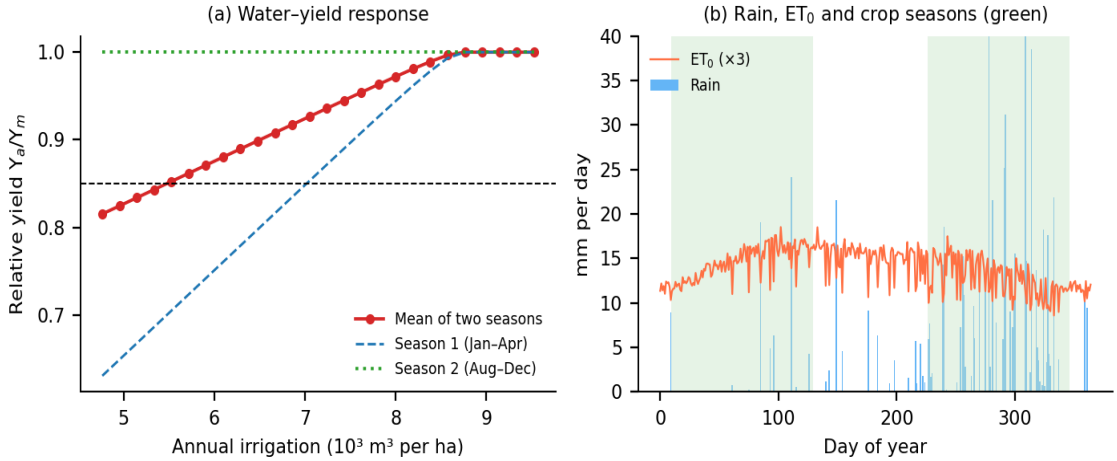



**Fig 3.** (A) Simulated Water–Yield Response to the Irrigation Ratio for the Two Seasons and (B) Daily Rain and Reference Evapotranspiration (×3) Over the Year; Green Bands are the Crop Seasons.

*Convergence and Quality of the Pareto Front*

**Fig. 4** compares NSGA-II with random search for the same number of simulations. The hypervolume of the NSGA-II archive rose rapidly during the first 20 generations and then slowly, reaching 0.982, whereas random search reached 0.963 after 6,480 evaluations, and the archive of the genetic algorithm filled to its limit of 300 designs after about 20 generations. The advantage is modest, partly because the problem has only five variables and a fast, smooth simulation, in which random sampling is not hopeless, and it appears mainly in the coverage of the front rather than in its extremes: both methods located the same minimum grid import (0.009 MWh) and the same minimum water (27.4 thousand m³), but the minimum net cost found by NSGA-II (2.61 lakh ₹) was 3.7 % below that of random search (2.71 lakh ₹). Random search also needed to retain all of its 256 non-dominated designs to compete, whereas NSGA-II concentrated the search on the front. The advantage of a guided search is expected to grow with more decision variables, such as crop-specific schedules, several tanks or hourly dispatch variables.

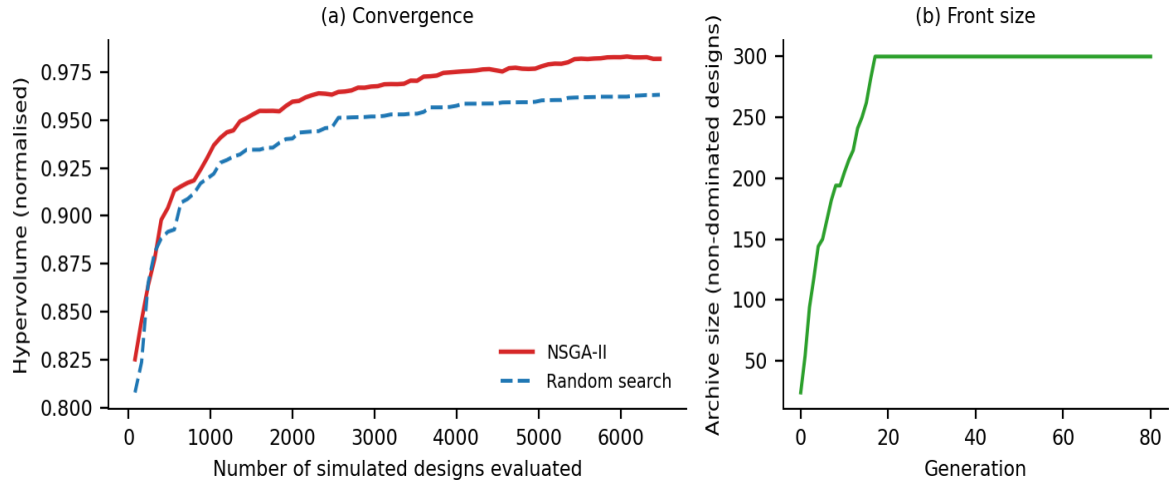



**Fig 4.** (a) Hypervolume Versus Number of Simulated Designs for NSGA-II (With Archive) and Random Search and (B) Size of the Non-Dominated Archive.

*Pareto Front and Trade-Offs*

**Fig. 5** shows the archived Pareto set in three two-dimensional projections. The three objectives conflict, but not equally. Water and net cost (**Fig. 5b**) were almost linearly related, because lowering the irrigation ratio below the agronomic buffer costs yield revenue much faster than it saves water, energy and water charges; the cost of saving water is therefore the revenue forgone, which averaged about ₹69 per m³ between the minimum-cost and the minimum-water designs and is far higher than any realistic water price. Cost and grid import (**Fig. 5a**) were in conflict mainly through the capital cost of PV and storage, as the grey cloud of random designs shows: the lowest import values were found only with large arrays and some storage. Grid import and water **(Fig. 5c**) were conflicting at the margin, because a deficit schedule reduces pumping energy, while the very low-water designs used less energy but did not necessarily have the lowest grid import.

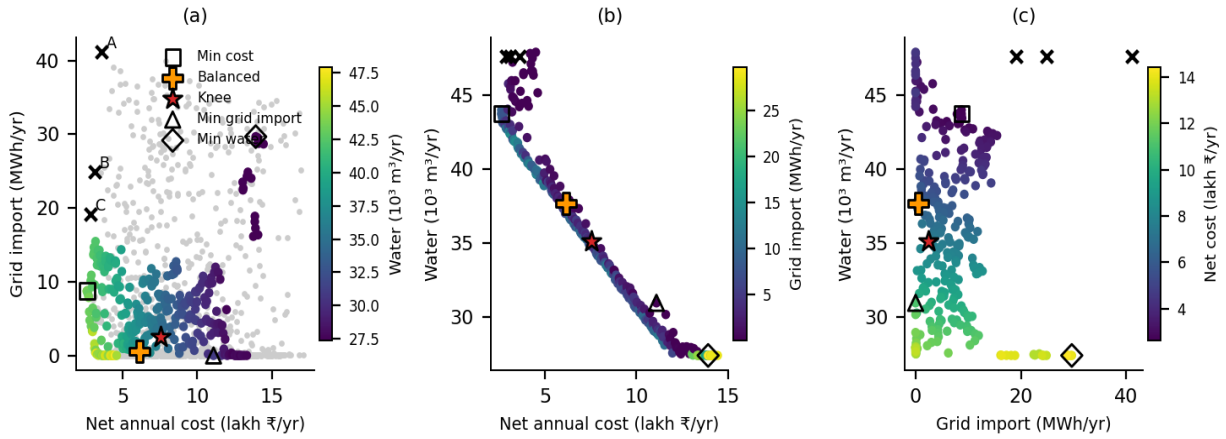



**Fig 5.** Pareto Projections (Colour: Third Objective). Markers Show the Minimum-Cost, Balanced, Knee, Minimum-Grid-Import and Minimum-Water Designs; Crosses A, B and C are the Conventional Baselines; Grey Dots are Feasible Random Designs.

**Table 3** gives the selected designs. The minimum-cost design installed 31 kWp of PV and a 176 m³ tank, no battery, an irrigation ratio of 0.92 and a solar schedule of 0.23. It reduced grid import to 8.7 MWh per year, which is 79 % below the grid-powered baseline A and 65 % below the conventional solar baseline B, and it lowered net cost to ₹2.61 lakh against ₹3.59 lakh, with no yield loss and 8 % less water, since the soil and rain buffer made a mild deficit costless. The balanced design (yield 0.950) saved 21 % of water and almost eliminated grid import (0.6 MWh) using 49 kWp of PV, a 29-kWh battery and a 26 m³ tank, at a net cost of ₹6.16 lakh that includes ₹3.3 lakh of forgone revenue. The knee design (yield 0.925) moved further along the front, and the minimum-grid-import design reached practically zero import (0.01 MWh) with 80 kWp of PV, but at a net cost of ₹11.1 lakh and with a yield of 0.88. The minimum-water design pinned the yield at the 85 % limit and the irrigation ratio at 0.57.

**Table 3.** Baseline and Selected Designs (Annual Values; Net Cost Includes the Revenue Lost to Yield Deficit)

| Design | PV (kWp) | Batt. (kWh) | Tank (m³) | *u* | φ | Net cost (lakh ₹) | Grid import (MWh) | Water ($10^3$ m³) | Rel. yield |
|---|---|---|---|---|---|---|---|---|---|
| A Grid pump | 0 | 0 | 0 | 1.00 | 0.00 | 3.59 | 41.1 | 47.6 | 1.000 |
| B Solar, no storage | 20 | 0 | 0 | 1.00 | 0.00 | 3.12 | 25.0 | 47.6 | 1.000 |
| C Solar + schedule | 20 | 0 | 0 | 1.00 | 0.60 | 2.86 | 19.2 | 47.6 | 1.000 |
| Min cost | 31 | 0 | 176 | 0.92 | 0.23 | 2.61 | 8.7 | 43.7 | 1.000 |
| Balanced | 49 | 29 | 26 | 0.79 | 0.54 | 6.16 | 0.6 | 37.7 | 0.950 |
| Knee | 43 | 16 | 81 | 0.74 | 0.49 | 7.53 | 2.5 | 35.1 | 0.925 |
| Min grid import | 80 | 37 | 191 | 0.65 | 0.34 | 11.09 | 0.0 | 30.9 | 0.884 |
| Min water | 3 | 41 | 449 | 0.57 | 0.08 | 13.91 | 29.7 | 27.4 | 0.850 |

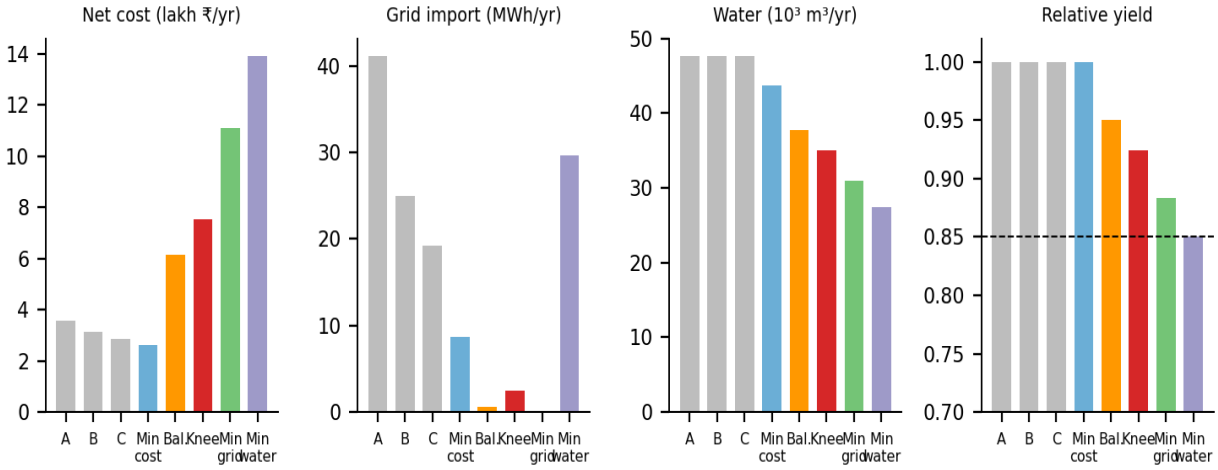



**Fig 6.** Comparison of Baseline Designs (Grey) and the Optimised Designs for the Four Objectives and the Relative Yield (Dashed Line: 0.85 Limit).

*Structure of the Optimal Designs*

The parallel-coordinate plot (**Fig. 7a**) illustrates the variation of the decision variables along the front. The median PV capacity of the 300 designs archived was around 37 kWp (range 3 – 80). The designs with the lowest grid import were the larger designs, with a mean PV capacity of around 50, while the designs with the highest grid import were the smaller designs, with a mean PV capacity of around 22. The irrigation ratio, which decreases from a mean value of approximately 0.9 for the cheapest designs to approximately 0.6 for the most expensive ones, and the solar schedule increases more than 0.4 in 63 % of the designs, demonstrates the worthiness of shifting the irrigation window to the solar window, as it is free of charge. The use of storage was varied. Some tanks hold up to 536 m³ of water, because pumping energy at the 65 m head is much cheaper than charging a battery to store the same energy: a 100 m³ tank will store the energy of 34 kWh stored in a battery, and cost a fifth as much to install, but only for the energy used in pumping it up to the 65 m head. The batteries were used only for the lowest import designs because they are the only way to provide the night-time load of the cold store. Above 50 kWh, the number of designs with a tank above 100 m³ was limited to 15 of the total 300 designs, indicating that the two stores are rather mutually exclusive in the budget for a particular design (**Fig. 7b**). Also, the open tank was a source of evaporation (approximately 12 m³ per year for the balanced design, but not a negligible amount, and would be worthwhile if the tank were refined to be enclosed).

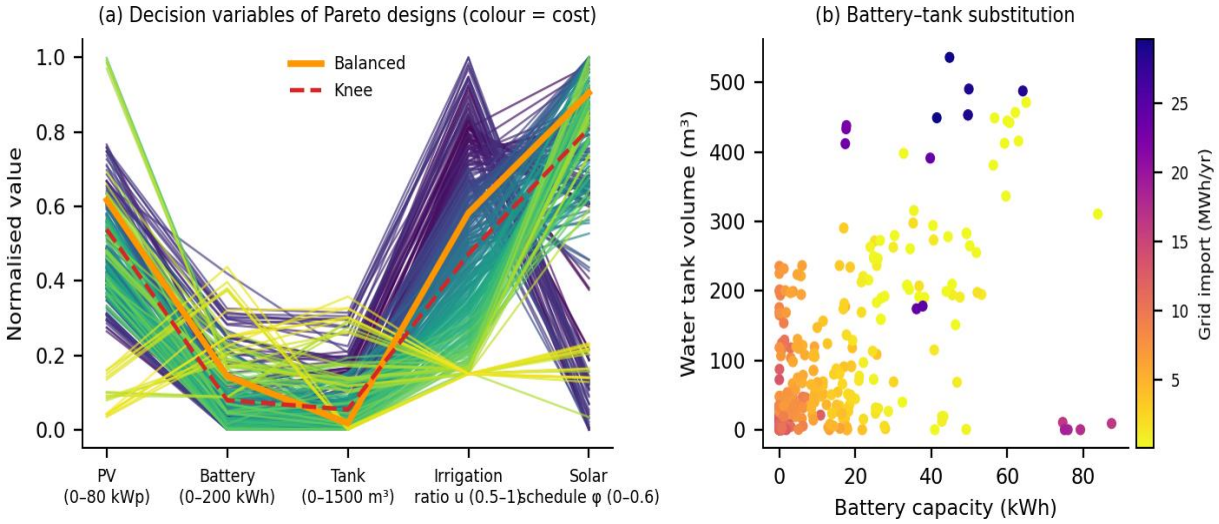



**Fig 7.** (A) Decision Variables of the Archived Pareto Designs (Colour: Net Cost; Thick Lines: Balanced and Knee Designs) and (B) Battery Capacity Versus Tank Volume (Colour: Grid Import).

**Fig. 8** presents the hourly performance of the balanced design during 5 days of the dry-season. A maximum of 36 kW was achieved during the array's operation, providing farm services and the midday irrigation, while the surplus PV energy was stored in the tank (26 m³ peak capacity) for the morning and evening irrigation windows, without pumping; when the battery was also installed, its operation covered the evening load, with limited periods of grid import. The dispatch rule is straightforward, and a predictive controller that anticipates cloudy days and fills the tank in advance of the weather, based on weather and soil-moisture predictions, would additionally reduce import.

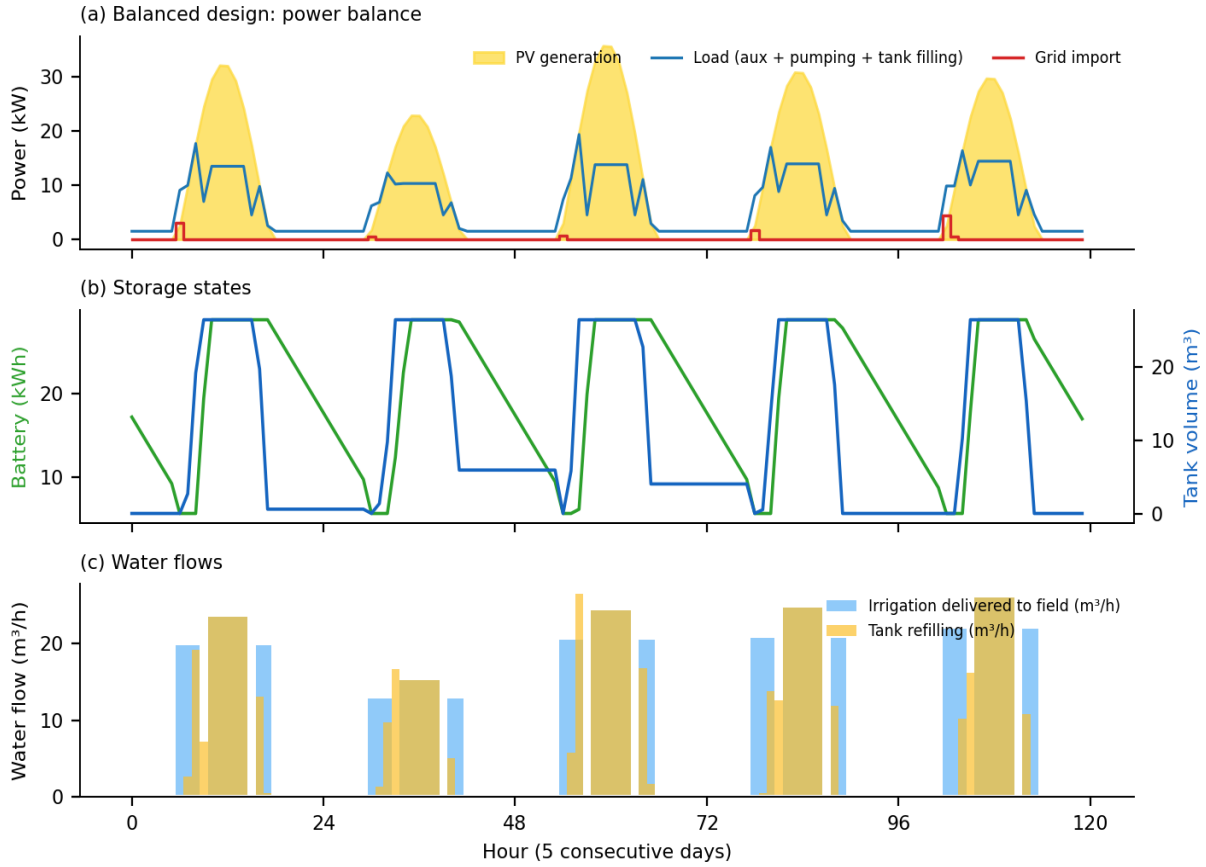



**Fig 8.** Hourly Operation of the Balanced Design Over Five Consecutive Days: (A) Power Balance, (B) Battery Energy and Tank Volume and (C) Irrigation Delivery and Tank Refilling.

*Water Productivity, Emissions and Self-Sufficiency*

**Table 4** summarises the resource-use indicators. Water productivity, the yield per unit of irrigation water, increased from 11.5 kg $m^{-3}$ in the baselines to 12.6 kg $m^{-3}$ for the minimum-cost design and 13.9 kg $m^{-3}$ for the balanced design, as an indicator that rewards the savings obtained by deficit irrigation [6]. Grid-related emissions fell from 29.2 t $CO_2$ per year (baseline A) to 6.2 t for the minimum-cost design and 0.40 t for the balanced design, and the share of the electricity demand met without the grid rose from zero to 78 % and 98 %. The large-array designs exported much more energy (72.8 MWh for the minimum-import design), which is worth only the low export tariff; where net-metering rules are less favourable or the export is capped, the optimum shifts toward smaller arrays and more storage.

**Table 4.** Resource-Use Indicators of the Selected Designs

| Design | Water productivity (kg $m^{-3}$) | Grid $CO_2$ (t/yr) | Self-sufficiency (%) | PV export (MWh/yr) | Tank evaporation ($m^3$/yr) |
|---|---|---|---|---|---|
| A Grid pump | 11.5 | 29.2 | -0 | 0.0 | 0 |
| B Solar, no storage | 11.5 | 17.7 | 39 | 11.0 | 0 |
| C Solar + schedule | 11.5 | 13.6 | 53 | 5.2 | 0 |
| Min cost | 12.6 | 6.2 | 78 | 11.5 | 81 |
| Balanced | 13.9 | 0.4 | 98 | 29.3 | 12 |
| Knee | 14.5 | 1.8 | 93 | 24.1 | 43 |
| Min grid import | 15.8 | 0.0 | 100 | 72.8 | 115 |
| Min water | 17.1 | 21.1 | 11 | 0.0 | 0 |

*Robustness to Weather and to Cost Parameters*

The designs were optimised for one synthetic year, so they were re-evaluated for a dry year (rainfall 339 mm, higher evapotranspiration) and a wet year (1019 mm), as shown in **Fig. 9**. In the dry year, the water withdrawal of every design increased (for the balanced design from 37.7 to 44.4 thousand $m^3$) and the net cost rose by 14 %, mainly because of yield loss: the relative yield of the balanced design fell from 0.950 to 0.938 and that of the knee design to 0.903, whereas the minimum-cost design, whose ratio of 0.92 leaves a higher margin, kept a relative yield of 0.999. The minimum-import design, with the lowest irrigation ratio, fell to 0.838 in the dry year, i.e. it violated the 85 % limit, which shows that designs at the edge of a constraint need a safety margin or adaptive irrigation. In the wet year the water use was lower and yield losses were smaller. Grid import of the minimum-cost design changed by less than 10 % between years, since PV production varied only modestly. A practical conclusion is that the irrigation ratio should be an adjustable operating parameter, set each season from the forecast, and that the PV and storage design should be chosen with the dry year in mind.

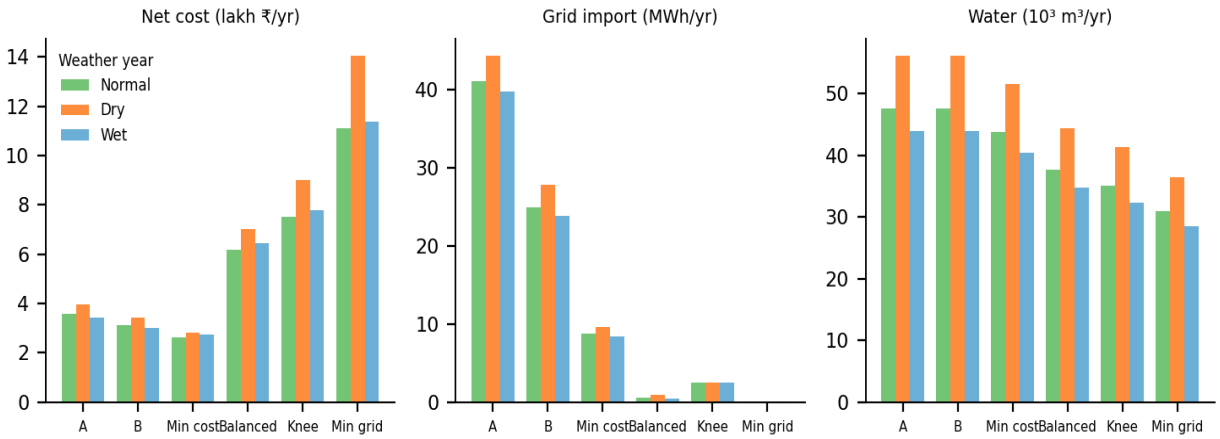



**Fig 9.** Net Cost, Grid Import and Water Withdrawal of Selected Designs in Normal, Dry and Wet Years (Designs Fixed from the Normal-Year Optimisation).

**Fig. 10** shows a one-at-a-time sensitivity analysis of the balanced design to ±20 % changes in the cost parameters. Net cost was most sensitive to the crop price (±10.7 %), because the revenue forgone in the yield deficit is the largest cost component, followed by PV cost (±7.5 %) and the discount rate (±5.5 %). Battery, tank, tariff and water-price changes moved the cost of the fixed design by less than 3 % each. Because the design was not re-optimised in this test, the results give an upper bound on the cost effect, and the design itself would change if, for example, the battery price fell substantially

or the water price rose steeply. A higher water price in particular would move the optimum toward lower irrigation ratios and more efficient scheduling.

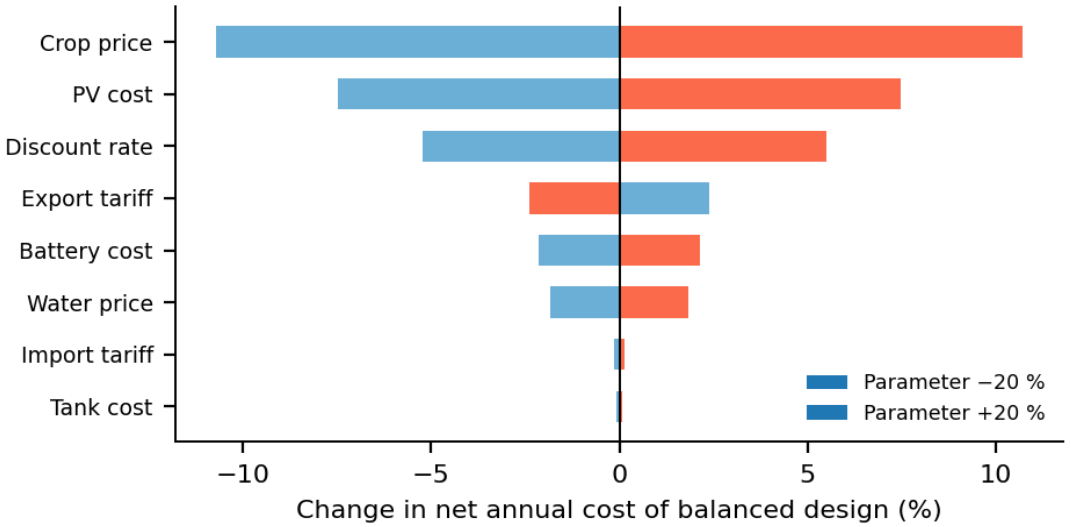



**Fig 10.** Sensitivity of the Net Annual Cost of the Balanced Design to ±20 % Changes in Cost Parameters.

*Field-Scale View of Crop Water Stress*

A deficit strategy must be judged also by how evenly the stress is distributed in the field, since non-uniform soils and emitters can turn a mild average deficit into severe stress in parts of the field. **Fig. 11** shows a simulated map of the first-season ratio $ET_a/ET_c$, a proxy for the crop water-stress index obtained from multispectral or thermal imagery, for a 500-plot field with spatially correlated soil water capacity (45–100 mm) and emitter uniformity. Under full irrigation the map was uniform (mean 1.000, minimum 0.99). With the balanced irrigation ratio of 0.79 the season-mean ratio was 0.87, and 6 % of the plots fell below 0.85, with light-textured parts of the field most affected, and the minimum-water ratio of 0.57 gave a mean of 0.69 with every plot below 0.85. Variable-rate irrigation zones, or the delivery of the deficit through the plots with the largest soil water capacity, would reduce this spatial penalty, and UAV or satellite stress maps could be used to adapt the ratio during the season. This result is specific to the simulated soil variability and is an illustration of how remote sensing can close the loop around the optimisation.

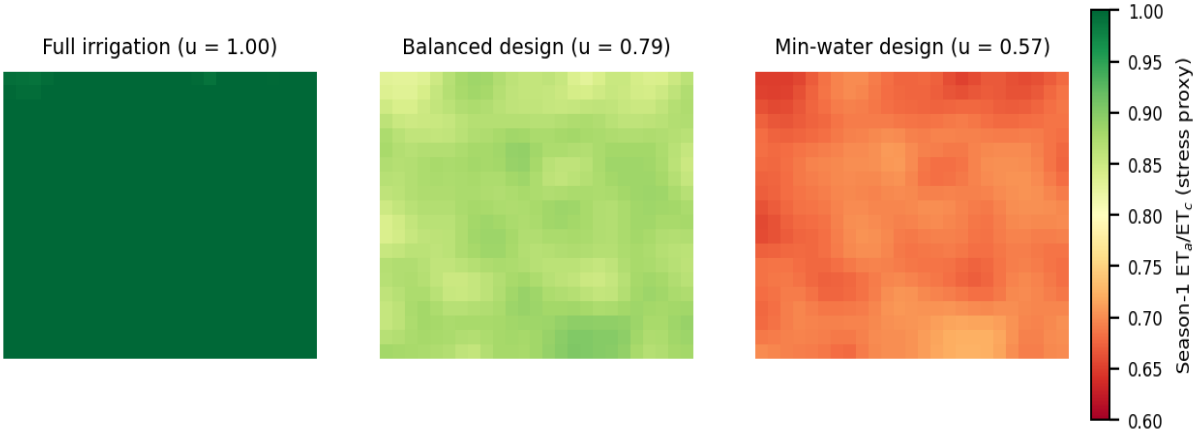



**Fig 11.** Simulated First-Season $Et_a/Et_c$ Maps (Stress Proxy) for Full Irrigation, The Balanced Design and the Minimum-Water Design Over a Field of 500 Plots with Soil and Emitter Variability.

*Implications for Farm Management and Policy*

Four messages emerge for growers and planners. First, schedule before storing: moving up to 60 % of the daily irrigation to the solar window cut grid import by 23 % relative to the unscheduled solar system B at no capital cost (baseline C), and drip irrigation, being tolerant of daytime application, makes this simple to implement with timers or soil-moisture controllers. Second, water storage is a cheap form of energy storage when water is needed, and its evaporation loss can be controlled by covering. Third, mild deficit irrigation (here about 8 % below the net requirement) is an almost costless water

saving in a climate with soil buffering and monsoon rain, but deeper deficits should be seasonal and monitored. Fourth, net metering and tariffs matter: in the optimisation, export at ₹2.5 against import at ₹7.0 favoured self-consumption and flexible loads. Policymakers who subsidise PV pumps without regard to the volume of water withdrawn risk encouraging over-pumping, because cheap energy lowers the marginal cost of water; combining PV subsidies with volumetric water limits, metering or price signals aligns energy and water objectives, and the Pareto approach used here quantifies the trade-off.
The weather is synthetic and one year was used for optimisation. The crop model is a linear soil-water bucket with a linear yield response, while the energy dispatch is a rule-based model. Costs, tariffs and prices are indicative only; the Indian agricultural electricity tariff, which is frequently subsidised, would affect the economics. It is assumed that the pump could function at any time of the day, with adequate inverter and grid and that the effects of borewell drawdown, pump curve, partial-load efficiency and power quality were not modeled. The size of the population was also small in order to fit the computing time usually available and more runs with larger populations and with several random seeds would be required to provide confidence intervals on the front. Future work will involve calibration of the model to an irrigation farm for which irrigation and soil-moisture and energy data are available; the use of stochastic optimisation over weather years; the incorporation of a crop planning variable; the incorporation of hourly dispatch variables; and testing of the recommended designs in a field pilot.

## IV. CONCLUSION

The study modeled the design and operation of an irrigated farm, powered by a solar collector, as a three-objective optimization problem - minimizing the net annual cost, minimizing the annual grid electricity import and minimizing the annual water withdrawal - subject to the constraint on the relative yield, of 85%. An equal simulation budget performed by an NSGA-II algorithm based on archives achieved a score of hypervolume 0.982 while random search achieved only 0.963. In comparison with grid powered farm with fully irrigated, the minimum cost design reduced the grid import by 79% and net annual cost by 27% without loss of yield. This balanced design reduced water withdrawal by 21% and grid energy use 99%, and reduced yield by 5%. Balancing energy and water needs was identified as strategies of solar-window irrigation scheduling, water-tank storage and deficit irrigation. The main advantage of battery storage was for designs aimed at being more grid independent. Robustness assessments showed that, for designs that were close to the yield constraint, they were sensitive to dry conditions and therefore needed to include a yield safety margin and adaptive irrigation practices. The findings demonstrated the value of jointly optimising energy, water, and economic performance rather than treating each resource independently. The resulting Pareto front provided alternative configurations for different operational priorities, supporting transparent design selection and informed decision-making for sustainable solar-powered agriculture.

**CRediT Author Statement**
The authors confirm contribution to the paper as follows:
**Conceptualization:** Meysam Smirnov; **Methodology:** Prabu Ragavendiran and Meysam Smirnov; **Software:** Prabu Ragavendiran and Meysam Smirnov; **Data Curation:** Meysam Smirnov; **Writing- Original Draft Preparation:** Prabu Ragavendiran and Meysam Smirnov; **Visualization:** Meysam Smirnov; **Investigation:** Prabu Ragavendiran and Meysam Smirnov; **Supervision:** Prabu Ragavendiran and Meysam Smirnov; **Validation:** Meysam Smirnov; **Writing- Reviewing and Editing:** Prabu Ragavendiran and Meysam Smirnov; All authors reviewed the results and approved the final version of the manuscript.

**Data Availability**
No data was used to support this study.

**Conflicts of Interests**
The authors declare no conflict of interest.

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**Competing Interests**
There are no competing interests.

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