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Groundwater safe yield powered by clean wind energy

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Abstract Wind energy has been used by humans for thousands of years. Yet, the relatively low economic cost and availability of fossil fuels upstaged the use of wind power. Fossil fuel resources are not renewable and will decline until exhaustion in the future. At the same time, humans have become aware of the adverse effects on the environment caused by reliance on fossil fuel energy. Wind, on the other hand, is a renewable energy source with minimal adverse environmental impacts that does not involve greenhouse gas emissions. Agricultural irrigation systems use fossil fuel energy resources in various forms. Groundwater withdrawal is central to supplying agricultural water demand in arid and semi-arid regions. Such withdrawal is mostly based on water extraction with pumps powered by diesel, gasoline, or electricity (which is commonly produced by fossil fuels). This paper coupled the non-sorted genetic algorithm (NSGA-II) as the optimization tool to the mathematical formulation of the wind-powered groundwater production problem to determine the potential of wind energy for groundwater withdrawal in an arid area. The optimal safe yield and the optimal size of regulation reservoir are determined considering two objectives: (1) maximizing total extraction of groundwater and (2) minimizing the cost of reservoir construction. The safe yield and the two objectives are optimized for periods lasting 1, 2, 3, 4, and 6 months over a 1-year planning horizon. This paper's methodology is evaluated with groundwater and wind-power data pertinent to Eghlid, Iran. The optimal safe yield increases by increasing the period length. Specifically, increasing the period length from 1 to 6 months increases the safe yield from 12 to 29 m^3. Application of the proposed NSGA-II-based optimization of groundwater production identifies the best design and operational variables with computational efficiency and accuracy.

Keywords Windmill · Safe yield of water release · Reservoir design · NSGA-II · Multi-objective optimization

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Introduction

Considering the non-renewable nature of fossil fuels and the side effects of greenhouse gas emissions in the environment, it is evident that using "clean and renewable” energy is a timely option. Research on the replacement of fossil fuels by renewable energy sources has shown that the initial costs of transitioning to renewable energies is high in comparison with the cost of relying on fossil fuels, yet, the present value of the costs of fossil fuel–based systems is higher over a 20-year project life time (Cloutier and Rowley 2011). Wind is a renewable source of energy, yet, it is weather dependent and geographically delimited (Loáiciga 2011). Unexpected changes of wind speed have led researchers to investigate the recurrent uncertainty for the purpose of energy production. Fripp (2011) presented a model to estimate the uncertainty in short-term forecasts of wind power. Several authors have assessed the wind energy potential and its possible applications in different locations of the world. Mohsen and Akash (1998), for instance, evaluated the wind potential for water pumping in Jordan and classified the sites according to their water yield; however, they did not assess the water-use efficiency. Lu et al. (2002) investigated meteorological and wind turbine data of the Hong Kong Islands with a simulation model to determine the annual power generation by wind turbines. They determined the wind turbines’ capacity factor (the ratio of actual annual power generation to the rated annual power generation) which was about 0.353 to 0.5 and confirmed the potential of wind power in that region. Al Suleimani and Rao (2000) stated that wind energy resources in Oman are adequate for groundwater extraction in remote locations. According to Keyhani et al. (2010), the wind energy potential in Tehran, Iran, is not sufficient for electricity generation, but it is adequate for rural energy supply, battery charging, and water pumping. Lara et al. (2010) established that about 17% of wind energy is usable for pumping water with most of the energy spent during the energy conversion process. Bhuiyan et al. (2011) used a web tool named Wind Energy Assessment (WEA) to analyze wind data at Kuakata, Bangladesh, from March through September, to determine the mean wind speed, shape factor, and scale factor. Simultaneously, they assessed the energy generated by a wind turbine with the rated capacity of 1 kW which was 2243 kWh per year, and compared the environmental benefits of wind power usage with the harmful emissions of coal power plants to show that advantages of using wind turbines for energy generation. A new algorithm which was based on the Weibull distribution was introduced by Brahmi and Chaabene (2012) to assess the wind potential in Sfax located in South-Eastern Tunisia, and determined the required wind turbine blade area considering the turbine elevation, the monthly wind energy, and the need of pumped water. Paul et al. (2012) demonstrated wind energy in southern Nigeria meets low-capacity electricity generation. Tahani et al. (2015) investigated the potential of wind and water energy to provide a part of electricity in Azadi sport complex in Tehran, Iran. They considered a 20-m-deep reservoir and two wind turbines and applied the GAMS software and a two-stage optimization method to optimize the benefit of applying hydroelectric energy to produce electricity and determine its use.

There are several strategies to utilize wind energy. Valdès and Raniriharinosy (2001) designed three wind-powered water pumps which are suitable to meet the Madagascar internal agricultural and lighting demands. Bakos (2002) investigated and confirmed low-price electricity generation using a wind–water power plant system. Badran (2003) confirmed the feasibility using wind turbines for pumping water in Jordan. Notton et al. (2011) considered a reservoir to store water in a pumped-storage system and suggested applying excess wind energy to pump water to higher elevation. Garcia-Gonzalez et al. (2008) recommended using Hydro Pumped-Storage units to generate power due to the variability and unpredictability of wind. Kusiak et al. (2009) considered five algorithms to monitor power from wind farms. The latter authors also combined data mining and evolutionary computation to develop a model for predicting and monitoring wind power. Senjyua et al. (2009) controlled the output power of wind turbine generators by regulating the pitch angle in small power systems. Sun et al. (2011) designed an optimal wind-powered water pumping system which can perform at variable wind speeds. The Weibull parameters were determined using Artificial Neural Network (ANN) in their model. Brown-Manrique et al. (2018) investigated micro-irrigation system powered by wind energy derived from windmills in Modesto Reyes town. The average wind speed at the cited town is 5.22 m/s which drives multi-blade windmills to produce 262.36 W and provide pumping power demand during 15.36 h daily. One 5000-l tank satisfies the water demand for irrigation by saving water while the wind speed is lower than a required threshold. Shaik et al. (2019) designed a water pumping system using a windmill and stated that wind energy, solar energy, and biomass are the best alternatives to fossil fuels due to their eco-friendly traits. Awad (2019) investigated the application of windmills to supply the water pumping power to cover the student services building's water needs. Results showed that the designed system can meet the water demands. Isaías et al. (2019) reviewed the application of renewable energy systems for irrigation of arid and semi-arid regions. The latter authors compared solar thermal pumping system, photovoltaic solar pumping system, and a wind pumping system. Their results demonstrated that there are technological limitations to solar thermal energy, but nevertheless photovoltaic solar energy has potential for pumping irrigation water in arid and semi-arid regions. The latter authors reported that wind power application to water pumping was more economical and viable than a diesel-based system in their study regions.

Assessing the potential and applications of the wind energy is a first step in determining its functionality and economic viability. Choosing the best application based on site-specific characteristics, the most appropriate equipment, and optimizing the operational schedules are paramount for the successful use of wind energy. Several authors have focused on optimizing the wind power potential and its applications. Many computational resources optimization methods such as evolutionary algorithm (EA), genetic algorithm (GA), non-dominated sorting genetic algorithm (NSGA-II), linear programming (LP), non-linear programming (NLP) etc., have been applied to optimizing wind energy generation and use (Bañosa et al. 2011). Vieira and Ramos (2009) developed an optimization model based on linear programming in MATLAB for maximizing energy efficiency in a water supply system, and established that relying on wind turbines as a power system was not justified economically. Kusiak et al. (2009) defined a multi-objective optimization model considering three objectives to evaluate the performance of wind turbines with an evolutionary algorithm. Mustakerov and Borissova (2010) developed a combinatorial optimization model to determine the wind turbine type, their number, and their placement in a wind park. Rao and Patel (2012) reported an application of the teaching–learning-based optimization (TLBO) algorithm for solving industrial environmental optimization problems. The TLBO algorithm does not require the specification of control parameters for its implementation. Ramoji and Kumar (2014) compared the GA-based optimization technique and TLBO optimization to minimize the costs of a hybrid energy system and concluded the GA-based method is better than TLBO algorithm. Keshtkar et al. (2015) presented simulation and optimization models to estimate the safe yield of groundwater withdrawal by wind turbines for irrigation purposes. Keshtkar et al. (2016) assessed the potential of wind energy to provide agricultural water in Eghlid, Iran, and defined an optimization model based on NLP methods to determine the optimized cropping pattern. Ahmed et al. (2017) investigated three renewable power systems (standalone photovoltaic (PV) system, standalone wind system, and standalone PV-wind hybrid system) in search of the best one for powering irrigation works in farms. The latter authors employed hybrid optimization by genetic algorithms) (HOGA) simulation software which is based on the genetic algorithm (GA) for sizing, optimizing, and economical evaluation of the three systems. The hybrid PV–wind system and the standalone PV system were sometimes superior depending on farm locations. Singh and Fernandez (2018) applied a new meta-heuristic algorithm called Cuckoo to solve a hybrid energy system optimization problem and compared it with GA and PSO algorithms. Sarzaeim et al. (2018) reported the TLBO algorithm was applied to determine the controlling parameters of the GA.

Previous research on wind energy has focused on assessing its potential by geographical location, improving wind turbines, and maximizing the efficiency of energy production. Few studies have focused on the use of wind energy for groundwater withdrawal and assessing the groundwater safe yield. The use of electricity from conventional grids is uneconomic in many areas due to geographical remoteness and accessibility costs. Under appropriate meteorological conditions, wind energy production may be feasible. It is factual that there are many arid and semi-arid regions that use groundwater resources to meet their water use employing fossil-fuel energy for water pumping. Fossil-fuel resources are non-renewable and their use leads to a variety of adverse environmental effects. Wind power, on the contrary, is a renewable alternative source of energy which is available in many regions and does not have significant harmful effects on the environment (see, e.g., Loáiciga 2011). Wind energy may be cost-effective compared to other sources to withdraw groundwater with wells for various uses. Windmills are relatively simple and generally cheap to generate wind power for small applications compared with the more complex turbines commonly used for commercial wind power generation. Windmills are relatively inexpensive to install and easier to use and maintain than their large-scale counterparts. The variability of suitable wind conditions means that wind power is best deployed when it is supplemented by reservoirs that store groundwater withdrawn during windy periods and supply water during non-productive periods. The reservoir size must be determined considering the patterns of water use. This work focuses on the analysis of groundwater withdrawal fueled by wind power. This study presents a methodology to calculate the amount of groundwater that can be withdrawn with windmills at suitable locations. The optimal reservoir storage size is determined to minimize storage costs and maximize the amount of water released from the reservoir. The optimal daily safe yield is determined over periods lasting 1, 2, 3, 4, and 6 months, and it is constant within each period. Thus, when the optimization period length equals 1 month, there are 12 optimized daily-safe yields over a 1-year planning horizon; there are six optimized daily-safe yields when the optimization period length equals 2 months over a 1-year planning horizon, etc. By defining different optimization periods, we can simultaneously determine their corresponding safe yields. The period safe yield is the discharge that is obtainable from a reservoir (connected to a groundwater extraction system) at all times within each period of analysis. Therefore, there is one optimized period-safe yield for each period length. For instance, the 1-month period safe yield equals the smallest among the 12 safe yields obtained for 1-month periods, and this amount of water release is available in any 1-month period of the year. Determination of different period-safe yields allows consumers to choose the kind of water use suitable for that location, such as agriculture, livestock, or other facilities where deployment of advanced energy technologies is not cost-effective. The safe yields are associated with optimized reservoir dimensions. The optimization scheme herein developed is solved with the NSGA-II multi-objective optimization algorithm relying on data from Eghlid, Iran.

Windmills

The use of wind turbines for well-water extraction is an old practice. They are driven by the passage of wind. Wind turbines consist of (1) a rotor of blades which are embedded on a central hub, (2) power transmission system which converts the rotational motion of the piston to reciprocating motion, and (3) a tower to hold the power transmission components at an appropriate height (Jain 2011). Wind turbines are classified as (1) power plant turbines and (2) non-power plant turbines (Jain 2011). Windmills are placed in the second category. They operate in the speed range of 2.5–15 m/s and can pump water from a range of depths in a reservoir. Among the advantages of windmills are (1) application of "clean renewable energy" and (2) low cost of groundwater extraction in windy places. Windmill components are shown in Fig. 1.

There are publications of the design and economic analysis of wind systems to irrigate areas in the arid and semi-arid regions. Kose et al. (2019) used a hybrid power generation system consisting of photovoltaic panels and wind turbine which are alternatives to diesel generators for pumping applications. Results indicated the net present value and internal rate of return of the project were US$7361 and 12.6%, respectively. Ssenyimba et al. (2020) applied solar–wind hybrid energy system to irrigate 1 acre of Nakytengu banana plantation in Kalanga. This system simulates flow behavior, static pressure, turbulence intensity, and stress at a speed three times the average wind speed in the Kalangala district elevated at 30 m above sea level. Khattab et al. (2020) reported an economic analysis of a stand-alone hybrid wind/PV/diesel water pumping system in Egypt. They compared different configurations considering PV only, PV with horizontal axis wind turbine, PV with vertical axis wind turbine, and PV with horizontal axis wind turbine and diesel generator, and diesel generator only. The cited works employed simulation approaches, without resorting to optimization of system design. This work couples a multi-objective optimization method with a mathematical model for wind-powered groundwater production.

Multi-objective optimization problems

Multi-objective optimization problems have two or more objective functions that must be satisfied jointly by choosing the best values of the decision variables. These problems are solved by obtaining a set of non-dominated solutions that are near the global optimum. A general equation for defining a multi-objective optimization model is as follows:

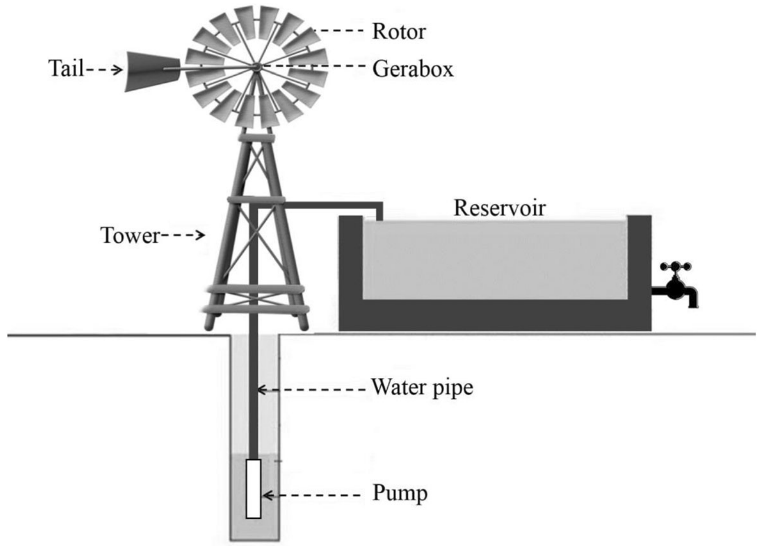

Fig. 1 Schematic of a windmill and its components

$$\text{Maximize or minimize } f(x) \quad x \in D \tag{1}$$

$$f : D \rightarrow R \tag{2}$$

where in Eq. (1) $f(x)$ = objective functions, x = vector of decision variables, and in Eq. (2), D = decision space and R = set of real numbers defined in Eq. (1).

Multi-objective problems can be converted to a single-objective problem by weighting the objectives. However, the weighting scheme introduces a subjective factor that biases the solution of the problem at hand. A non-subjective approach to solving multi-objective problems is the search for a set of non-dominated solutions among all possible solutions. In the case of two objective functions, the non-dominated solutions can be plotted as a production possibility frontier (PPF, or Pareto front, after the Italian economist Vilfredo Pareto, 1848–1923), whose points represent combinations of the values of the objective functions with the best tradeoffs among objectives that are achievable for the problem being solved.

Multi-objective evolutionary algorithms

Evolutionary algorithms can be applied to solve any well-posed optimization problem. Bozorg-Haddad et al. (2009, 2010) and Sabbaghpour et al. (2012) employed the HBMO algorithm to solve optimization problems. Fallah-Mehdipour et al. (2013, 2014) applied genetic programming in groundwater modeling. The NSGA-II is a well-known evolutionary algorithm which has been used to solve many multi-objective water optimization problems (Jahandideh-Tehrani et al. 2019). The NSGA-II evolutionary algorithm is applied in this study to solve the optimization model.

The non-dominated sorted algorithm (NSGA-II)

The first step of the genetic evolutionary algorithm (GA) (see Srinivas and Deb 1994) generates an initial random population of potential solutions (called chromosomes) and the objective functions are evaluated for this initial population of chromosomes. The next population of chromosomes is determined based on the evaluation results using the last iteration's chromosomes obtained from crossover and mutation operators. Therefore, the generated population of chromosomes (the current tentative solutions) in each iteration of the GA is superior to that of the previous iteration and an evolutionary trend is created leading to a near-optimal solution.

The steps of the NSGA-II are as follows:

(a) Generate a random population of tentative solutions (chromosomes) with a uniform distribution and in the form of a C × V matrix. C and V represent respectively the decision variables (called genes) and chromosomes (these are the solutions or values of the objective functions evaluated with the current genes). The dominant and non-dominant solutions form several Pareto fronts.

(b) Classify the chromosomes of the calculated Pareto fronts with the following equation:

$$d_{I_j} = \sum_{n=1}^{No} \frac{f_n^{I_{j+1}^n} - f_n^{I_{j-1}^n}}{f_n^{\max} - f_n^{min}} \quad (3)$$

where in Eq. (3), d_{I_j} = crowded distance of the j-th solution, No = the number of objectives of the optimization, $f_n^{I_{j+1}^n}$ and $f_n^{I_{j-1}^n}$ = the values of the n-th objective functions, the index I_j^n = denotes the j-th solution calculated for the n-th objective in the ranked list of Paretos, and $j-1$ and $j+1$ = indices of two close solutions. Also, f_n^{max} and f_n^{min} = the maximum and minimum values of the n-th objective function for the solutions of the generated population.

The NSGA-II algorithm searches for the closest solutions (those with high values of d_{I_j}) which lead to Pareto fronts comprising a wide range of decision-making. As shown in Fig. 2, the Pareto fronts are ranked from best to worst by how distant they are from an ideal Pareto front.

(c) Select chromosomes (or solutions) using a tournament selection operator. The tournament operator compares the solutions considering (1) their non-dominancy rank and (2) their crowding distance (a measure of the density of solutions in the neighborhood). If a solution prevails over others, it is selected as a parent; otherwise, a solution with the longest crowding distance is chosen as the best solution. Deb and Agrawal (1995) implemented a Simulated Binary Recombination (SBX) Crossover operator to combine two chromosomes and generate a new one (child chromosome). This operator is similar to the cut crossover in binary data sets. The following equations calculate a probability distribution:

$$P(\beta_i) = \left\{ \begin{array}{ll} 0.5(\eta_c+1)\beta_i^{\eta_c} & , if \ \ \beta_i \le 1 \\ 0.5(\eta_c+1)\dfrac{1}{\beta_i^{\eta_c+2}}, & otherwise \end{array} \right\} \quad (4)$$

$$\beta_i = \left\{ \begin{array}{ll} (2u_i)^{\frac{1}{\eta_c+1}}, & if \ \ u_i \le 0.5 \\ \left(\dfrac{1}{2(1-u_i)}\right)^{\frac{1}{\eta_c+1}}, & otherwise \end{array} \right\} \quad (5)$$

where in Eq. (4), $P(\beta_i)$ = the crossover probability, β_i = the difference between the objective functions of the parent and child, and η_c = constant which represents the difference between parent and child. The probability of generating close solutions to the parent increases with increasing η_c. u_i = a random value within the range [0, 1]. The difference between parent and child chromosomes is calculated with the following equations:

$$\beta_i = \left| \frac{x_1^{child} - x_2^{child}}{x_1^{parent} - x_2^{parent}} \right| \quad (6)$$

$$x_1^{child} = 0.5\left[(1+\beta_i)x_1^{parent} + (1-\beta_i)x_2^{parent}\right] \quad (7)$$

$$x_2^{child} = 0.5\left[(1-\beta_i)x_1^{parent} + (1+\beta_i)x_2^{parent}\right] \quad (8)$$

where in Eq. (6), x_1^{child} and x_2^{child} = values of the first and second child chromosomes, respectively. Also, x_1^{parent} and x_2^{parent} = values of the first and second parent chromosomes, respectively.

The other operator is mutation. The polynomial mutation operator suggested by Deb and Goyal (1999) is applied in this paper:

$$\delta_i = \left\{ \begin{array}{ll} (2r_i)^{1/(\eta_m+1)} - 1 & , \ if \ \ r_i < 0.5 \\ 1 - \left[2(1-r_i)^{1/(\eta_m+1)}\right] & , \ if \ \ r_i \ge 0.5 \end{array} \right\} \quad (9)$$

where in Eq. (9), δ_i = the quantity of mutation, r_i = a random value in the interval [0, 1], and η_m = the constant of the mutation distribution. The mutation operator δ is added to the gene value as follows:

$$x^{child} = x^{parent} + \delta \quad (10)$$

A new generation of combined children and parent chromosomes is produced by evaluation of the objective functions using the genes' values. These chromosomes are ranked and those with the highest ranks are selected to be part of the next generation. Chromosomes with lower grades are added to complete the new generation whenever the number of selected chromosomes is less than the population size. This keeps the population size from one generation to the next constant.

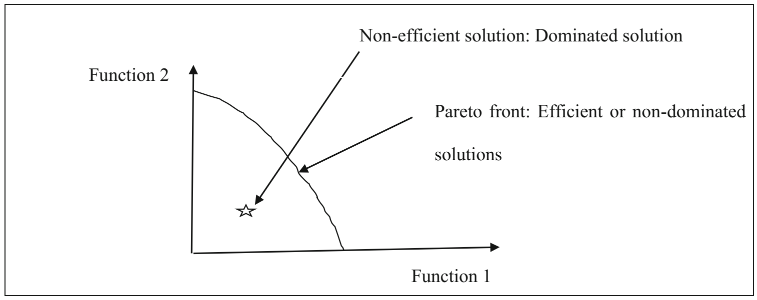

Fig. 2 Pareto front for a production-maximizing problem with two objective functions

Methods

The wind speed distribution is variable. Seasonal and monthly changes in wind speed are larger than those of daily changes. Reservoirs are constructed to store the pumped water during high wind speed and meet water use during low wind speeds, thus allowing the optimal use of wind energy for groundwater pumping. The larger the reservoir, the greater the volume of water that can be stored. At the same time, the larger the reservoir, the more costly its construction. In view of these tradeoffs, we consider two optimization objectives: (1) determination of the daily-safe yield so that the total regulated water (i.e., the total water released from the reservoir) is maximized and (2) minimizing the reservoir construction costs. These two objective functions are written as follows:

$$Obj:\begin{cases} f_1 = Maximize\,(Sum(\mathrm{Re}(t))) \\ f_2 = Minimize[(a\times b)+[(a+0.3)\times(b+0.3)-(a\times b)]\times h_{\max}] \end{cases} \tag{11}$$

in which the first objective function refers to maximizing the total regulated water (*sum (Re (t))*), and the second minimizes the construction costs. Also, f = the objective function, Re = the daily safe yield in period t (m^3), a = the length of the reservoir (m), b = the width of the reservoir (m), and h_{max} = the reservoir height (m) which was set equal to 3 m. The daily safe yield is defined as the maximum daily discharge that is obtainable from a reservoir (connected to a groundwater extraction system) in any day of a period of given length (say, 1 month). Considering short planning periods would lead to low safe yield when there is low wind speed leading to low pumping rate during several months of the year. Increasing the length of the planning period may increase the safe yield and, thus, water regulation. Therefore, the safe yield and reservoir size are determined considering five different planning-period lengths, that is, 1, 2, 3, 4, and 6 months. The water released from the reservoir is set constant in all days of any period, and this is the daily safe yield with respect to windmill performance and reservoir storage. Thus, the daily safe yield is defined as the largest volume of water that can be released every day in a period of specified length. Another pertinent variable in our analysis is the period safe yield which is equal to the smallest optimized daily safe yield for a period of specified length (in this study, the period lengths are 1, 2, 3, 4, and 6 months). The determination of the period safe yield for, say, a 4-month period is shown in Fig. 3. There are three 4-month periods in 1 year, and each of them has a daily safe yield. It is seen in Fig. 3 that the three 4-month periods extend from day 1 through day 120, from day 121 through day 240, and from day 241 through day 360. Their corresponding daily safe yields equal 23, 55, and 67 m^3/day, respectively, as shown in Fig. 3. The smallest among them is 23 m^3/day, and this is therefore the period safe yield corresponding to 4-month periods. The period safe yields for 1-, 2-, 3-, and 6-month periods are determined analogously. The decision variables for the five planned-period lengths are listed in Table 1. The achievable wind energy and the available amount of pumped groundwater must be calculated prior to optimizing the safe yield. A simulation model was developed for the purpose of calculating the wind energy usable for extracting groundwater.

Simulation model

The wind power formula is as follows (Jain 2011):

$$P_t = \frac{1}{2}\rho A v^3 \tag{12}$$

where P_t = generated power (W) at time t, ρ = air density (1.23 kg/m^3), A = the rotor area (m^2), and v_t = wind speed (m/s) at time t.

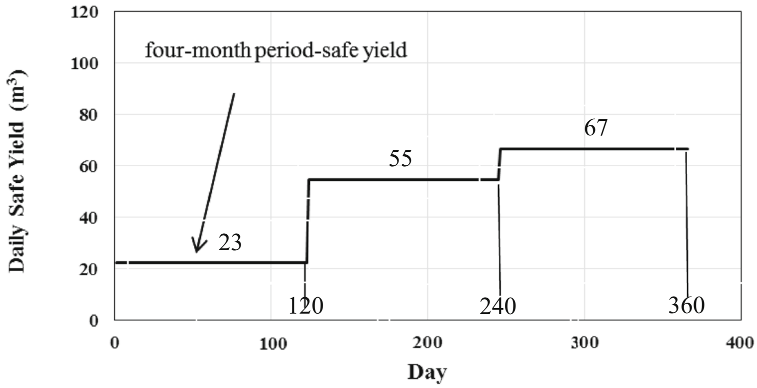

Fig. 3 The period safe yield for a 4-month period equals the smallest daily safe yield among the daily safe yields corresponding to the three 4-month periods in 1 year, which is equal to 23 m^3/day in the graph. The three 4-month periods are those between day 1 and day 120 (daily safe yield equals 23 m^3/day), between day 121 and day 240 (daily safe yield equals 55 m^3/day), and between day 241 and day 360 (daily safe yield equals 67 m^3/day) as depicted in this figure

The wind turbines considered in this work are windmills, which produce rotational mechanical energy by the action of wind. Windmills require minimum maintenance and are simple to operate. They operate in a range of wind speed from 2.5 through 15 m/s. The groundwater discharge (water pumping rate) is defined as follows (Keshtkar et al. 2015):

$$Q_t = (P_t \times \eta_t)/(\gamma \times HT_t) \tag{13}$$

$$\eta_t = \eta(M)_t \times \eta(E) \tag{14}$$

$$\eta(M)_t = \begin{cases} 0.25 & if \quad 2.5 \le v_t < 4.5 \\ 0.50 & if \quad 4.5 \le v_t < 8 \\ 1.00 & if \quad 8 \le v_t < 15 \end{cases} \tag{15}$$

where Q_t = pumping rate (m^3/s) at moment t, HT_t = head of lift (m) at time t, and η_t = total efficiency at time t which consists of the mechanical efficiency $\eta\,(M)_t$ and the energy efficiency$\eta\,(E)$. According to the Betz law (1919), the maximum obtainable energy from wind turbines is 59% which is the energy conversion efficiency (Jain 2011). Therefore, $\eta\,(E)$will be equal to 0.59, γ = specific weight of water (N/m^3). The head of lift equals the sum of the depth to groundwater (measured from the ground surface) and the elevation of water in the reservoir above the ground surface, as shown in Fig. 4.

$$HT_t = HR_t + HG_t \tag{16}$$

where HR_t = the elevation of the water level in the reservoir above the ground surface at time t (m), and HG_t = the depth to groundwater at time t (measured from the ground surface) (m), which is assumed constant.

The water-balance equation in the reservoir is given by Eq. (17) (Keshtkar et al. 2015):

$$S_{t+1} = S_t + Q_t' + \mathrm{Pr}_t - Loss_t - \mathrm{Re}_t - Sp_t \tag{17}$$

Table 1 Decision variables and their numbers corresponding to five optimization period lengths

Time period (month)	Decision variables and their numbers in each time period: Length of the reservoir (a) (m)	Width of the reservoir (b) (m)	First volume of water in the reservoir (m^3)	Daily safe yield (m^3)	Total number of variables
1	1	1	1	12	15
2	1	1	1	6	9
3	1	1	1	4	7
4	1	1	1	3	6
6	1	1	1	2	5

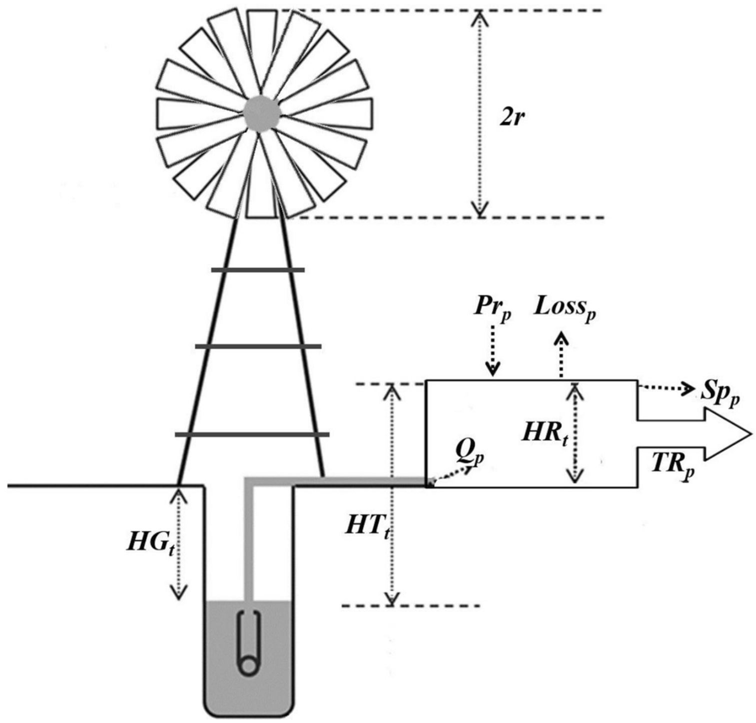

Fig. 4 Schematic of the variables present in the mathematical model developed in the study

where S_t = the volume of water in the reservoir at time t, S_{t+1} the volume of water in the reservoir at time $t + 1$, Pr_t = volume of precipitation during period t, $Loss_t$ = the volume of water evaporation from the reservoir during period t, Re_t = the volume of water released from the reservoir during time t, Sp_t = the volume of water spilled from the reservoir during period t, and $Q_t' = Q_t \times t$ represents the volume of groundwater discharge to the reservoir during period t. All the variables in Eq. (17) are expressed in cubic meters. Precipitation and evaporation are minor, thus they are neglected in Eq. (17).

The simulation model was coupled with the GA multi-objective toolbox of MathWorks (1993) and applied to five periods whose durations are 1, 2, 3, 4, and 6 months. The daily safe yield is determined for each period setting it constant during each period. Figure 4 shows the variables of the simulation model.

Case study

Eghlid city in Fars province of Iran was chosen as a case study. This city is placed in a mountainous region and has cold winters and mild summers. Minimum and maximum temperatures of this city are respectively − 22 and 37 °C. The average annual precipitation ranges between 300 and 330 mm within the city and between 400 and 600 mm in its villages and highlands. The wind speed in Eghlid is considerable most of the year. Wind speed data for Eghlid from April 2007 through April 2008 are shown in Fig. 5. These data are presented in 10-min intervals and were measured 10 m above ground. It is seen in Fig. 5 that the average wind speed in the second half of the year is more suitable for windmill operation than that of the first half. Therefore, the water withdrawal is preferable in the second half of the year. Windmills come with different rotor sizes. The possible pumping rate for each size of windmill rotor is set by the manufacturer. The groundwater depth in Eghlid is 40 m. A 12-foot windmill with the rotor diameter equal to 3.6 m was chosen for this study.

Results and discussion

The simulation-optimization model was run for the 1-, 2-, 3-, 4-, and 6-month periods. The optimal values of the daily safe yield and reservoir dimensions were determined for these five periods. In the case of 1-month periods, there are 12 optimized daily safe yields, i.e., one for each month of the year, plus the reservoir width, the

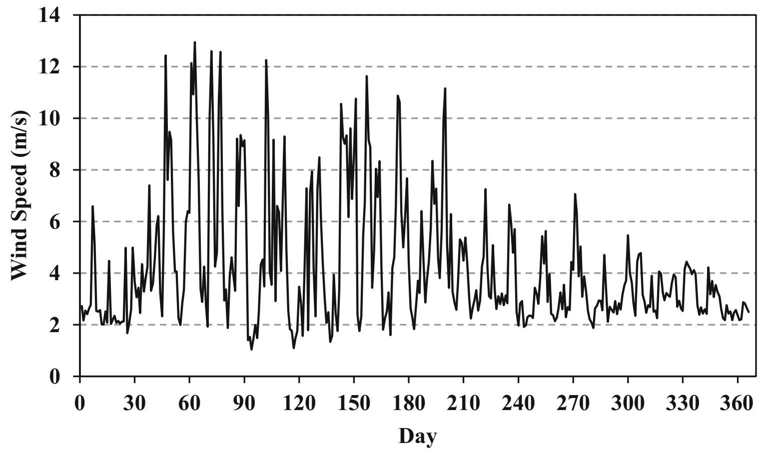

Fig. 5 The average daily wind speed at 10-m elevation in Eghlid, Iran

reservoir length, and the initial volume of stored water in the reservoir, for a total of 15 decision variables. In the case of 2-month period, there are six daily safe yields (there are six 2-month periods in 1 year) plus the reservoir width, the reservoir length, and the initial volume of water stored in the reservoir for a total of nine decision variables. This accounting establishes that the number of decision variables for 1-, 2-, 3-, 4-, and 6-month periods equal 15, 9, 7, 6, and 5, respectively, as listed in Table 1. The calculated daily safe yields are the same for all days of each period duration (i.e., 1 month, 2 months, etc.), but differ among periods.

Sensitivity analysis tests were done to find the optimum and final GA parameters by considering different combinations of algorithm parameters and using them in different iterations. By comparing the indexes of resulted Pareto fronts, the best combination parameters were determined. The Pareto fronts obtained from 10 different optimization runs are shown in Fig. 6 for the five period lengths. Figure 7 depicts the daily safe yields for each period length. Recall the period safe yield equals the smallest among the daily safe yields corresponding to a specific period duration. For instance, Fig. 7 shows the 12 daily safe yields corresponding to a 1-month period that can be obtained over a 1-year planning horizon. The smallest and largest among the 12 yields equal 12 and about 100 m^3/day, respectively. The period safe yield equals the smallest among the 12 daily safe yields because it is the only one that can be achieved in any 1-month period over a 1-year horizon. Similar comments apply to the other the 2-, 3-, 4-, and 6-month periods. By comparing all five periods, it is seen in Fig. 7 that the maximized period safe yield increases with increasing period length. This is because long periods include more days with high and low wind speeds than short periods, which means that the largest water withdrawal is larger and the smallest water withdrawal is smaller in long periods than in short periods. By choosing a suitable reservoir size, there are more options to store and release water, thus producing higher period safe yields as the period length increases. It is also seen in Fig. 7 that short periods may have larger daily safe yields than long periods due to few days with low wind speed in some months. For instance, Fig. 7e shows that the maximal 6-month daily safe yield is less than the maximal safe yields of shorter periods. That is because there are more days with low wind speed in a 6-month period than in shorter periods. The best and worst obtained values of the objective functions, period safe yield, and reservoir dimensions are listed in Table 2 for two optimal Pareto points. The period safe yield values for 1-month, 2-month, 3-month, 4-month, and 6-month periods are respectively equal to 12, 15, 21, 23, and 29 m^3. It can be seen that increasing the period length increases the period safe yield from 12 to 29 m^3. The point of the Pareto front at which the sum of safe yields is a maximum is the most desirable point associated with the objective of maximizing water release from the reservoir (see Fig. 6 and Table 2). In fact, this point defines the optimal reservoir size to regulate water storage and maximize the releases. Recall the wind speed range of the windmills is 2.5–15 m/s. It is seen in Fig. 5 that in several days of the year the average daily wind speed is slower than 2.5 m/s or faster than 15 m/s which interrupts windmill functioning. Therefore, there is no water production in those days. A suitable reservoir must provide at least 12

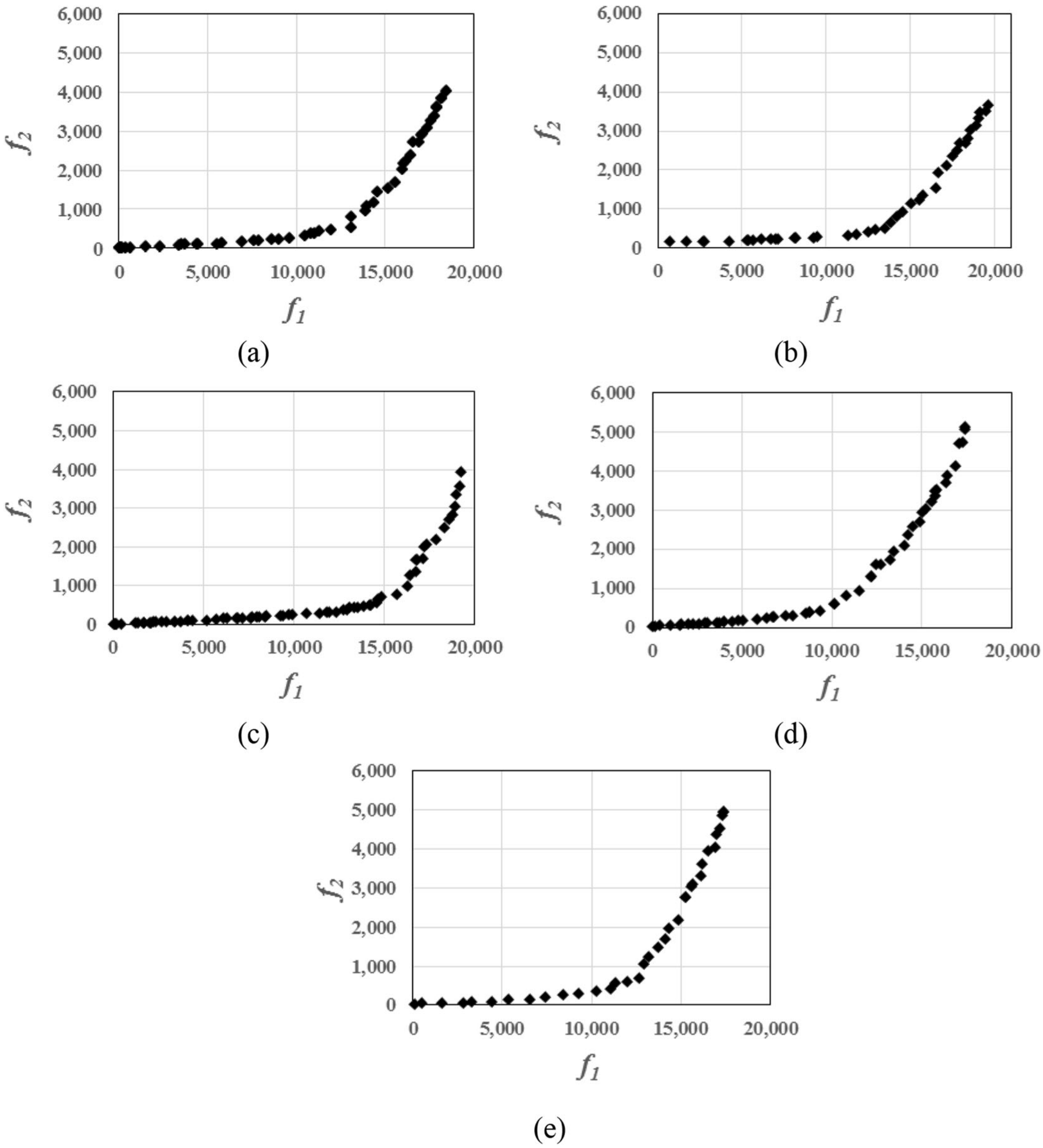

Fig. 6 Pareto fronts obtained from 10 optimization runs corresponding to (**a**) 1-month, (**b**) 2-month, (**c**) 3-month, (**d**) 4-month, and (**e**) 6-month periods

m^3/day of water in a 1-month period. The optimal determined reservoir length and width values to achieve the maximum 1-month period-safe yield are respectively equal to 64 and 60 m. In contrast, the minimum point of the Pareto front at which the reservoir dimension is minimum is the most desirable point given by the objective of minimizing the reservoir construction costs. The best and worst values of the two objectives are helpful for planning of groundwater withdrawal at the considered location. Based on the water demand and the conditions in any month, one can choose suitable Pareto front points and the corresponding reservoir dimensions. In addition, the determination of the daily and period safe yields in different time periods would allow farmers to choose the best crop pattern for the available water. It is seen in Table 2 that the number of generated populations in 4-month and 6-month periods are 1000 and 500, respectively. Recall the number of decision variables time periods (listed in Table 1) were 5 and 6 s in 6- and 4-month periods, respectively. Therefore, the solutions were achieved faster for these two periods than for shorter periods.

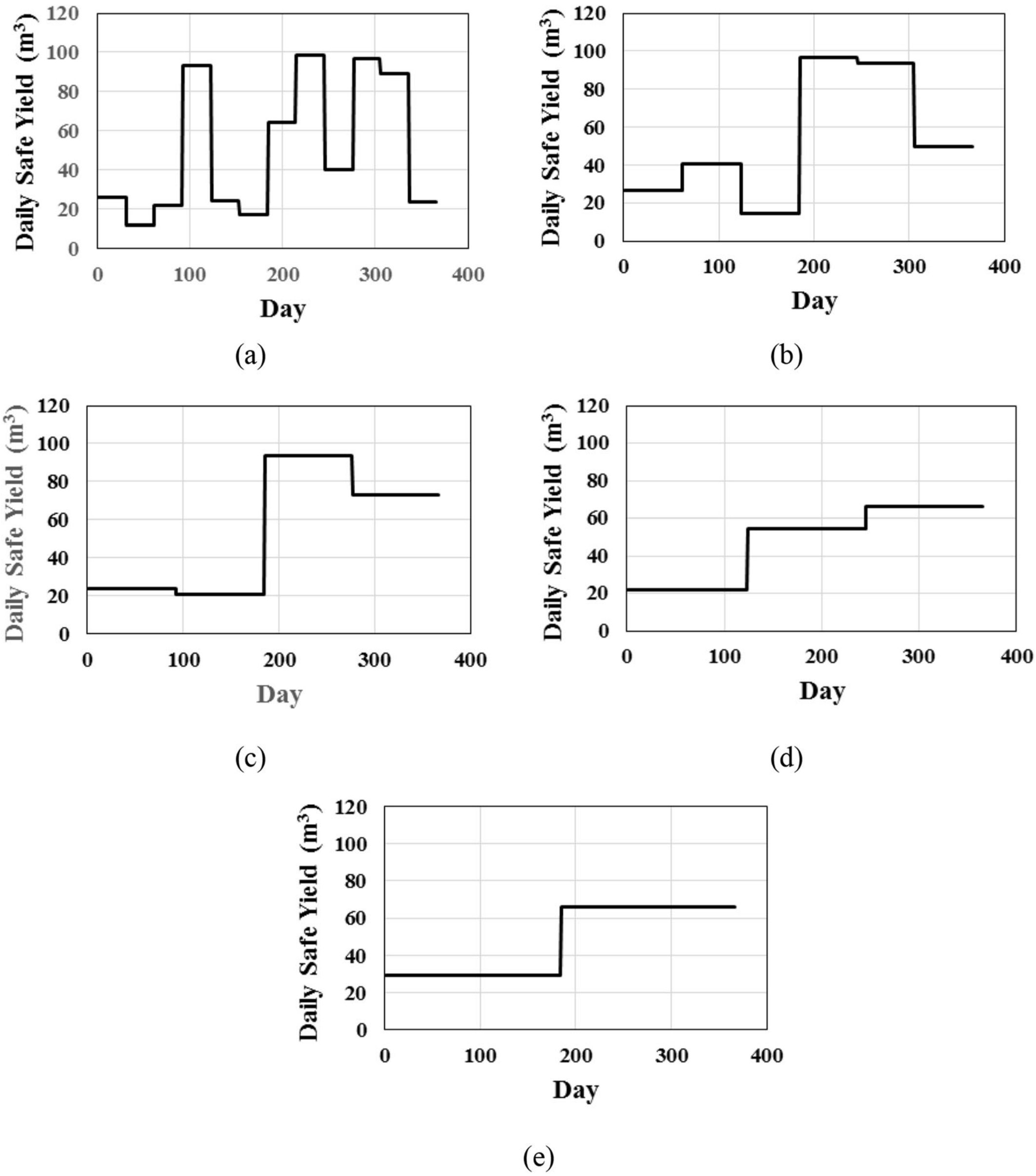

Fig. 7 Daily safe yields corresponding to (**a**) 1-month, (**b**) 2-month, (**c**) 3-month, (**d**) 4-month, and (**e**) 6-month periods. The period safe yield corresponds to the smallest among the safe yields calculated for a given period length

Concluding remarks

This study investigated the application of windmills to extract groundwater, how to regulate it with a reservoir, maximizing the daily and period safe yields, and minimizing the reservoir construction costs over a 1-year planning horizon. A mathematical model was developed to calculate the water pumping rate, water storage in a reservoir, and its distribution in different periods. Concerning the different water demands in different times of the year for variable crops, five different periods of lengths equal to 1, 2, 3, 4, and 6 months were employed to optimize reservoir size and maximize the safe yield. This choice of planning periods helps consumers in selecting the best reservoir size and determining the water supply that best fits the feasible cropping patterns for agricultural purposes. This paper's results provide users with alternative applications of wind energy depending on the region and the chosen safe yield. In locations with a wide range of daily safe yield, this

Table 2 The best and worst objective function values, period safe yield, and reservoir dimensions corresponding to two Pareto points and five optimization period lengths

Periods	Population size	Number of generations	f_1 Objective function (m^3)	Reservoir length (m)	Reservoir width (m)	Period safe yield (m^3/day)	f_2 Objective function (m^3)
1 month	100	1000	Best = 18,466	64	60	12	Worst = 4006
			Worst = 19	0.9	0.3	0.01	Best = 1.8
2 months	100	1000	Best = 19,621	70	50	15	Worst = 3639
			Worst = 731	10	10	0.3	Best = 121
3 months	100	1000	Best = 19,297	89	43	21	Worst = 3940
			Worst = 81	1	1	0.2	Best = 3
4 months	100	500	Best = 17,425	75	66	23	Worst = 5104
			Worst = 48	1	1	0.1	Best = 3
6 months	100	500	Best = 17,346	72	66	29	Worst = 4855
			Worst = 98	1	1	0.24	Best = 3.2

paper's method can be applied to seasonal applications of windmills, or to add generators and batteries to store wind energy when the reservoir becomes full during periods of high wind speed. The stored energy can be used during times of low wind speed to supply power needed for groundwater production. The NSGA-II multi-objective optimization algorithm was implemented to solve the dual-objective optimization problem. The Pareto fronts of 10 different runs for five time periods were obtained with the associated optimal safe yields and reservoir sizes. Our results show that increasing the period length from 1 to 6 months increases the period safe yield from 12 to 29 m^3. The calculated reservoir dimensions are much larger in 4- and 6-month periods compared with other period lengths. Using larger reservoirs may save water during periods of high wind speed and allow improved regulation of water use during low-wind-speed periods. This would increase the period safe yield. This holds true until the reservoir capacity meets the maximum possible water storage, yet, this situation would be infeasible economically. Depending on the crop pattern, it may not be necessary to release water for agriculture in some periods of the year. Alternative water uses may increase the water owner's income and render groundwater production driven by wind energy more attractive. The best objective function value concerning minimizing the reservoir construction cost satisfies the least water release allowed, which is the worst objective function concerning the maximizing objective. Regarding the two objective functions, one can choose points on the Pareto fronts that yield various optimal combinations of reservoir cost and safe yield. Increasing the number of the windmills would increase the safe yield. Topics for future research are (1) comparing solutions on the Pareto fronts according to water consumption patterns, (2) assessing possible projects and their economic feasibility with respect to the choice of planning periods concerning the period safe yield, (3) determining agricultural decision variables in association with the safe yield, and (4) choosing the number of windmills and their type.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no competing interests.

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