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Optimal Determination of the Q/A Factor for Parabolic Concentrator Solar Collector Networks

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This work presents a study of the Q/A factor in optimised designs of solar thermal networks of the Solar Heat for Industrial Processes (SHIP) type, which utilise Parabolic Trough Collector (PTC) technology for both winter and summer seasons. A MINLP optimisation problem with 9 decision variables is solved using the heuristic technique of Particle Swarm Optimization (PSO) coupled with a proposed and validated transient thermohydraulic-economic model. The inlet temperature of the Heat Transfer Fluid (HTF) was varied across low, medium, and high ranges, along with the target temperature and thermal load required by the process. For predicting the Q/A factor, a multivariable polynomial regression using Artificial Neural Networks (ANN) was employed. It was found that the HTF inlet temperature and the temperature required by the industrial process are the variables that most significantly impact the Q/A factor. The average optimised Q/A factor values are lower than the commonly used factor of 0.7 $kW{\cdot}m^{-2}$, resulting in 0.51 ± 0.03; and 0.65 ± 0.03 $kW{\cdot}m^{-2}$ with deviations of 26.54 % and 7.30 % for winter and summer.

1. Introduction

Over the past two decades, the Q-A ratio (Q/A) has been increasingly adopted as a standardized parameter for converting the area of solar thermal collectors into installed capacity. This ratio, typically valued at 0.7 kW/m^2, has gained widespread acceptance over time. (Solar Heating and Cooling Programme International Energy Agency, 2004). The value of this factor is 0.7 $kW{\cdot}m^{-2}$ and is considered valid for stationary solar thermal collectors such as unglazed collectors, flat plate collectors, and evacuated tubular collectors. In 2023, this factor's value was also adopted for single-axis tracked concentrating collectors (line focusing systems) and two-axis tracking systems (Solar Heating and Cooling Programme International Energy Agency, 2023). Consequently, for statistical purposes, the established Q/A value was extended to Parabolic Trough Collectors (PTC). The success of this category of concentrators lies in their great flexibility to operate across a wide temperature range, from 50°C to 400°C (Kalogirou, 2019).

Different research studies have been conducted on the design of solar thermal networks using PTC technology to define the most suitable design methodology. Rodríguez et al. (2024) carried out a thermoeconomic study on solar thermal generation with PTC and Linear Fresnel Collectors (LFC) at low and medium temperature levels in the dairy industry in Spain (120-180°C). They found that the percentage of thermal energy utilization, as well as the size and location of the solar plant, are decisive parameters affecting the cost of solar thermal energy generation. In another study, Mohammadi et al. (2021) performed an environmental thermoeconomic sensitivity analysis to evaluate the performance of a 5 MWth nominal capacity plant composed of PTC collectors, located in Salt Lake City, Utah, USA, using the System Advisor Model (SAM) software. The researchers determined that the optimal solar multiple (SM) value is 1.5, with a capacity factor of 35.1% and a levelized cost of heat (LCOH) of $26.3/MWth. The initial investment in a solar field installation significantly influences the project's economic performance. Additionally, the researchers compared the LCOH of the solar thermal network to a conventional process using natural gas, and they found the SHIP plant to be economically competitive. Akar et al. (2023) simulated a hybrid plant consisting of flat plate solar collectors (FPSC) and PTC. The hybrid solar thermal network was modelled in the SAM platform and successfully validated with a real hybrid solar district located in Taars, Denmark. The researchers assessed current and future renewable thermal energy systems

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(RTES) technologies in autonomous and hybrid configurations through techno-economic and environmental studies. The analysis yielded positive and feasible results, particularly at low and medium temperature levels. Rosales-Pérez et al. (2024) utilised the TRNSYS platform to conduct an energy and economic analysis in order to determine the potential of hybrid plants composed of FPSC and PTC. They compared the performance of these hybrid systems to solar thermal networks consisting of only one of these collector types. Their findings revealed that hybrid systems achieve higher solar fractions and lower levelized costs than individual cylindrical parabolic collector systems. Additionally, hybrid systems require smaller solar field areas compared to individual flat collector systems. Tao et al. (2023) conducted a multi-objective optimization using a genetic algorithm from an exergetic-economic perspective in a solar-assisted integrated multi-energy generation system for the analysis of electrical costs in three cities in Iraq. On the other hand, Eskandari (2023) used a thermoeconomic optimization to determine the optimal operating conditions considering exergy as an objective function in a hybrid solar-geothermal plant that generates electricity, heating, and cooling, achieving a probable increase in exergy of 33.8%. Immonen and Powell (2022) used optimization to optimize the operating conditions of a solar thermal plant composed of PTC technology, achieving a reduction of 6.6% in the levelized cost of heat, an increase in plant efficiency of 7.5%, and a reduction of emissions by 22.2% compared to the base case. The use of the Q/A parameter for quick estimation of the installed area and for statistical purposes as a sizing factor with a value of 0.7 kW·m2 has become widespread over time. Most research in this field that reports solar thermal networks is characterised by this factor. Schoeneberger et al. (2020) reported on SHIP plants installed in the USA, all of which are characterised by the Q/A factor. Similarly, Epp and Oropeza (2017) present a list of SHIPs, each comprised of various technologies, all standardized by the Q/A factor. However, there are some studies reporting SHIP plants with Q/A values not standardised to the proposed value. Kalogirou (2003) reported a range of Q/A from 0.264 to 0.527 kW·m^2 in his investigation of solar thermal networks using simulation on the TRNSYS platform, including stationary equipment such as flat plate solar collectors and mobile concentrators like the PTC. Dür and Monika (2023) provide information about 19 SHIP-type solar thermal networks installed in various countries, with areas exceeding 5,000 m^2; and with the Q/A factor ranging from 0.53 to 0.67, averaging 0.681 kW/m^2. From the above, it is clear that while the Q/A value of 0.7 is a quick way to estimate the solar collection area for PTC-type systems, it requires understanding in relation to parameters such as thermal load, inlet temperature, and target temperature. In this study, an analysis of the Q/A factor is conducted for optimized designs of PTC solar thermal networks in the scenarios of summer and winter seasons in Guanajuato City, Mexico. The analysis involves varying the inlet fluid temperature (HTF) within low and medium ranges, as well as the temperature and thermal load required by the process within typical operating ranges. The analysis employs a coupled transient thermohydraulic-economic model using the heuristic optimisation methodology of Particle Swarm Optimization (PSO). The objective is to determine the Q/A factor, derived from the acquisition of the equipment geometry, network size and structure, and from the operational conditions that maximize economic benefits with the smallest possible installed area.

2. Methodology

The thermo-hydraulic-economic model used in this research was presented and validated in the work by Lizárraga-Morazan and Picón-Núñez (2024), which, due to space constraints, is not reproduced here. The methodology includes a one-dimensional transient model for the thermo-hydraulic solution coupled with the economic analysis model of Present Value of Life Cycle Energy Savings (PVLCES). The Mixed-Integer Nonlinear Optimisation (MINLP) problem is presented below:

$$Max\ Z = \left[\frac{PVLCES}{A}\right]$$

Subject to the following restrictions:

$$h(\bar{x}) = 0$$

$$g(\bar{x}) \leq 0 \qquad (1)$$

Where *A* represents the area of the thermosolar network. The objective function includes the two most important parameters in the design of thermosolar networks: the economic parameter that must be maximised, represented by the PVLCES, and the area parameter which must be minimised. *h(x̅)* represents the set of equations that constitute the extended thermo-hydraulic-economic model for the thermosolar network, while g(x̅) is the set of constraints imposed on the system and is represented by the following expressions:

$$1.1 \geq sf \geq 1$$

$$T_o^{max} \leq T_{HTF}^{lim} \qquad (2)$$

$PVLCES \geq 0$

Where T_o^{max} is the maximum instantaneous outlet temperature delivered by the thermosolar network during the daily operation time (9 – 18 h); T_{HTF}^{lim} is the limiting operating temperature of the heat transfer fluid (HTF), and sf the solar fraction defined by the following expression:

$$sf = \frac{Q}{Q_p} \tag{3}$$

Where Q_p represents the thermal load required by the process. Q is the total useful integrated heat, which represents the total energy harvested by the system at the temperature level required by the process (T_{obj}). This value results from the integration of the instantaneous useful energy gained by the heat transfer fluid (HTF) during the operation time.

$$Q = \int_{t=9\,h}^{t=18\,h} q_t dt \tag{4}$$

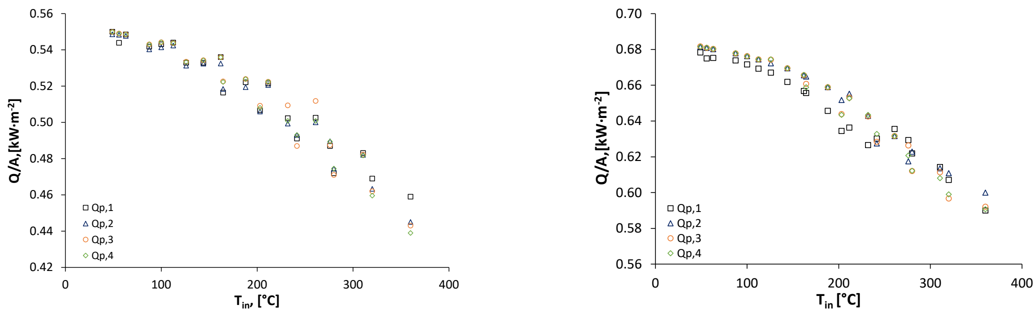
In the optimisation problem, nine decision variables were considered. These variables include the dimensions defining the geometry of a Parabolic Trough Collector (PTC): length (L_c), aperture width (W_{aper}), receiver diameter (D_i), glass envelope diameter (D_{gi}), and the focus of the PTC (f). Additionally, it incorporates variables defining the size and structure of the network, such as the number of collectors per line (N_{cl}) and the total number of lines in the network (N_L). Lastly, the model also optimizes the mass flow rate of the working fluid ($\dot{m}_f$) and the choice of fluid. Four commonly used commercial fluids were considered for analysis: pressurised water, Syltherm-800 (Dow, 1997), Therminol VP-1(Eastman, 2019), and Dowtherm-A (Dow, 2023). To solve the optimization problem, the stochastic methodology of Particle Swarm Optimization (PSO) was employed. In this technique, potential solutions are treated as particles with memory, allowing them to recognize the best solution within the feasible search space (Sharma et al., 2012; Afzal et al., 2023). The optimization problem was solved by varying the thermal load required by the process (Q_p), the inlet temperature of the heat transfer fluid (T_{in}), and the temperature required by the process (T_{obj}). Wide intervals were employed for typical winter and summer days. The ranges are: Q_p (kW), 400 - 4,000; T_{obj} (°C), 70 – 400; T_{in} (°C), $(0.7-0.9)T_{obj}$.
The parameter search space is as follows: L_c (m), 2-15; W_{aper} (m), 0.5-9.3; D_i (m), 0.01-0.08; D_{gi} (m), 0.1-0.2; f (m), 0.2-3; N_{cl}, 1-40; N_L, 1-200; $\dot{m}_f$ (kg·s^{-1}), 0.1-10; HTF: Syltherm-800, Dowtherm-A, Therminol, VP-1, pressurized water. The selected decision variable limits are derived from commercial equipment reported in open literature (Meyers, 2013).
To have a representative sample of the ranges of the independent variables, specific values were selected for Q_p, T_{in} and T_{obj} that covered the defined intervals. The thermal load of the process was divided into four levels: 400, 1,600, 2,800, and 4,000 kW. The target temperature was divided into 7 levels: 70, 125, 180, 235, 290, 345, and 400 °C, and the inlet temperature was divided into three levels: 0.7, 0.8, and 0.9·T_{obj}. The optimisation problem was solved for each of the 84 combinations of Q_p, T_{in} and T_{obj} levels, and for each season. Daily instantaneous environmental data on irradiance, ambient temperature, and wind speed collected in the city of Guanajuato (21.0190° N, 101.2574° W) at the facilities of the University of Guanajuato, Mexico, were employed. The results obtained regarding the geometry of the PTC equipment that makes up the network, the size and structure of the network, and the optimized operating conditions are reported in the work by Lizárraga-Morazan and Picón-Núñez (2024). The optimised Q/A factor is obtained from the following expression using the optimised design results:

$$Q/A = \frac{Q}{N_L N_{cl} W_{aper} L_c} \tag{5}$$

The optimized Q/A data were plotted with respect to the independent variables.

3. Results

In Figure 1, the optimized Q/A results are plotted with respect to the inlet temperature for both winter and summer seasons. In general, the value of the optimized Q/A factor decreases with respect to the increase in the inlet temperature of the heat transfer fluid (HTF). The average value of Q/A is 0.51 ± 0.03 kW·m^{-2} for winter and 0.65 ± 0.03 kW·m^{-2} for summer.

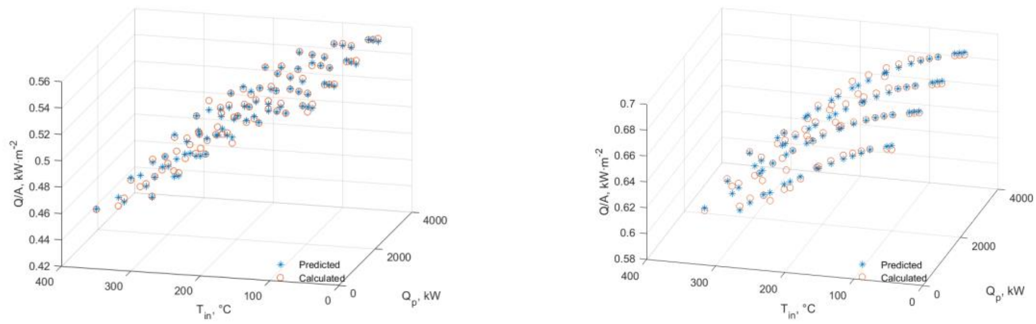


(a) (b)

Figure 1: $Q/A - T_{in}$ profiles: (a) Winter, and (b) Summer

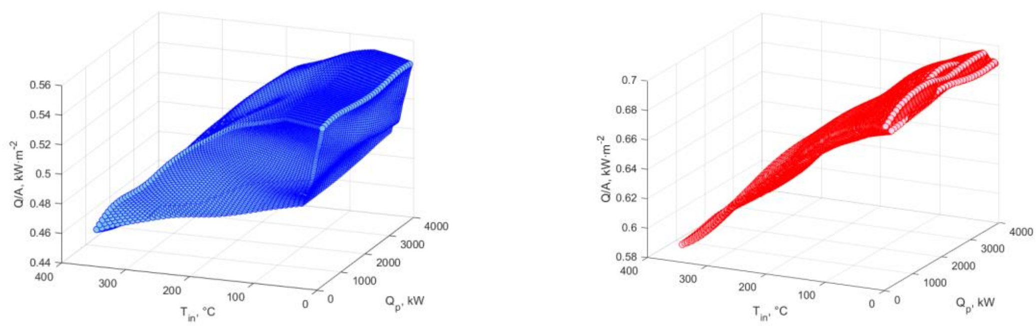
To predict the Q/A values in both seasons, non-linear multivariable regressions with neural networks were performed. The best fit was achieved using a neural network with 3 neurons in the input layer and 20 perceptrons in the hidden layer. The Levenberg-Marquardt algorithm was employed with a sigmoidal activation function. Training was conducted using 70 % of the dataset, while the remaining 30 % was proportionally split for validation and testing. The Mean Squared Error (MSE) values were 6.0889×10^{-10} and 3.484×10^{-7} $kW^2 \cdot m^{-4}$, and the correlation coefficient (R) was 1.0000 and 0.9997 for the winter and summer seasons. Figure 2 graphically presents the regression fit.

In Figure 3, the profile of the Q/A factor is depicted in relation to the inlet temperature and the energy required by the process. Among the two independent variables, the inlet temperature has a greater impact on the Q/A factor, and it affects it negatively.



(a) (b)

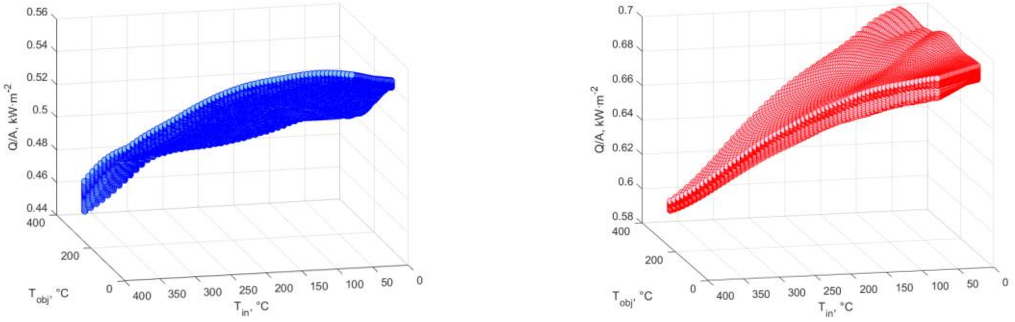
Figure 2: Q/A fit (a) Winter, (b) Summer



(a) (b)

Figure 3: Q/A - T_{in} - Q_p profile: (a) Winter, (b) Summer

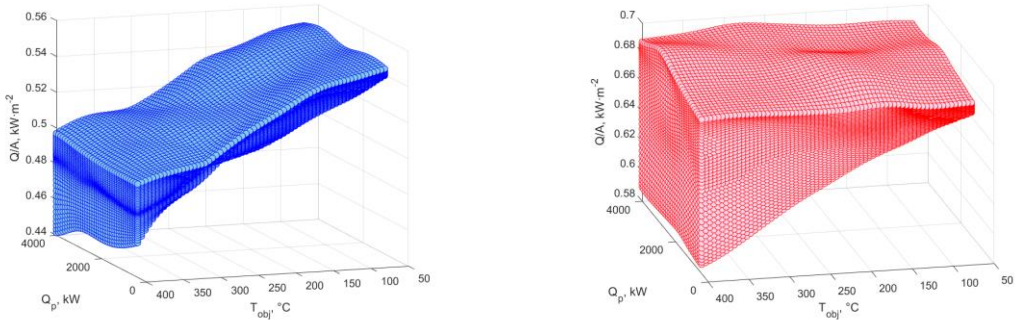
In Figure 4, the performance of the Q/A factor is plotted with respect to the inlet temperature and the temperature required by the process. The latter has a higher impact in winter.



(a) (b)

Figure 4: Q/A - T_{in} - T_{obj} behavior (a) Winter, (b) Summer

Figure 5 presents the profile of the Q/A factor with respect to temperature and the energy required by the process.



(a) (b)

Figure 5: Q/A - Q_p - T_{obj} profile (a) Winter, (b) Summer

4. Conclusions

This study investigates the values of Q/A that results from optimised designs with the aim of finding the values that can be used in sizing of PTC plants for rapid estimations. From the results, the following conclusions can be drawn:

a) The average value of Q/A is 0.51 ± 0.03 kW·m^{-2} for winter and 0.65 ± 0.03 kW·m^{-2} for summer. These values apply for thermal load ranges between 400 kW and 4,000 kW and target temperatures ranging from 70°C to 400°C.
b) The average values of the optimised Q/A factor are lower compared to the standardised factor of 0.7 kW·m^{-2}, with a deviation of 26.54 % and 7.30 % for winter and summer. Based on these results, the use of the standardised factor would lead to under designed systems that would not meet the required thermal load of the process. This situation is more pronounced during the winter season.
c) The inlet temperature of the heat transfer fluid (HTF) significantly impacts Q/A. Specifically, at higher inlet temperatures, the Q/A value decreases.
d) Both the inlet temperature T_{in} and the target temperature (T_{obj}) substantially affect the Q/A value. In particular T_{in} has a more pronounced impact during summer than in winter while effect of T_{obj} is more significant during winter.
e) Interestingly, T_{obj} emerges as the most influential variable in determining Q/A. In the winter, as T_{obj} increases, the Q/A value decreases almost linearly. Notably, during summer, across all levels of T_{obj}, the maximum Q/A value achieved is 0.68.

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