Design of a hybrid solar / induction heater optimized by artificial intelligence

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***Abstract*—A water heater is a thermodynamic device that uses different sources of energy, among them electricity, fuels and solar energy. However, under certain conditions, these technologies have advantages and disadvantages. In this article, the design of a hybrid heater is proposed, with which it is sought to take greater advantage of solar energy and as a backup system, in the face of climatic adversities, magnetic induction technology. The design is optimizedfor maximize the water temperature and in turn minimize the amount of electrical energy consumed, improving the efficiency of the heater. To achieve this, different tools are used, such as simulation, computational physics and artificial intelligence.**

***Index Terms*—SEED, EDA, Computational Physics, Thermodynamics, Solar Heater, Magnetic Induction.**

I. INTRODUCTION

A water heater is a thermodynamic device that uses energy to increase the temperature of the water. Among the different sources of energy, electricity, fuels (mainly gas and oil derivatives) and solar energy stand out, which have been successfully implemented in the industry. However, under certain conditions, these technologies have advantages and disadvantages. For example, heaters using solar energy can achieve an efficiency of 94 to 96% during the transfer of solar energy (J. Subramania, 2018), keeping the water temperature between 65 and 105 ° C on a sunny day, however, when the weather conditions are not suitable (for example, snow, cloudy days or rain), that efficiency drops drastically.

On the other hand, there are heaters that use fuels, such as natural gas or hydrocarbons (Haines, Kyriakopoulou, &

Lawton, 2019). Despite the fact that these types of devices are commonly used in homes and for industrial processes, their long-term daily use is not favorable for the environment, due to the high emissions of polluting gas. In addition, the rise in fuel prices makes them unprofitable systems (Sahnoune, Madani, Zelmat, & Belhamela, 2014).

Regarding the systems that use electrical energy, in the industry can be find two types of heaters, those of resistance and those of magnetic induction. This type of device is capable of heating water to a temperature of 35 ° C in an approximate time of three minutes, achieving an energy transfer efficiency of 98 to 99% (PAHohne, 2019); However, resistance devices have a high electrical power consumption, approximately 1 to 1.5 KW / h, an amount that is penalized in some countries, therefore, their daily use is not favorable (Balke, Healy, & Ullah, 2016). On the other hand, in the state of the art it has been reported that magnetic induction devices consume less electrical power, therefore,

Based on the aforementioned, an alternative to solve the problem of water heating is to design hybrid systems that implement efficient and environmentally friendly technologies. Therefore, in this article the design of a hybrid system is proposed, with which it is sought to take greater advantage of solar energy and as a backup system (in the event of climatic adversities) electromagnetic induction technology.

Designing a water heater under a hybrid approach is challenging, as there are several factors to consider. However, two substantial problems that must be dealt with are pointed out:

1) Define the type and size of the coil and solenoid.
2) Define what is the optimal volume of water heating to minimize the consumption of electrical current.

To solve these problems, the physics that prevails in the heat transfer process must be modeled, both solar and inductive. And in turn, the interaction between the two approaches must be optimized. To do this, this article proposes to carry out the design of the hybrid heater through the use of artificial intelligence, specifically employing a computational optimization algorithm with an evolutionary approach called SEED (detailed in Section 3.1). This type of algorithms have been widely used in the state of the art to carry out the design of electrical systems (Masuda, Okamoto, & Wakao, 2019; Naar & Bay, 2013), however, there are fewer works where they are implemented for thermodynamic design .

Broadly speaking, a scheme is proposed that provides a series of candidate solutions to the problem, whose efficiency is measured through a cost function, which models the interaction between solar and inductive technology. The values obtained by the cost function for each of the candidate solutions feed back to artificial intelligence, allowing it to generate better and better solutions to solve the problem.

Next, a series of concepts are shown to understand the proposal in detail.

II. Theoretical framework

A. Solar heater

At present, there is a high demand for fossil fuels, as well as electricity and combustion gases, however, this demand has generated the scarcity of these natural resources, which faces the costs for the consumer, these natural resources are used for heating water in domestic, industrial and service uses. On the other hand, the consumption of fuels for heating water, in many cases generates greenhouse gases or pollutants. As an alternative to fossil fuels, the use of solar energy as a source of energy transfer has been proposed. In Figure 1, the general proposal of the hybrid solar / induction water heating system is shown.

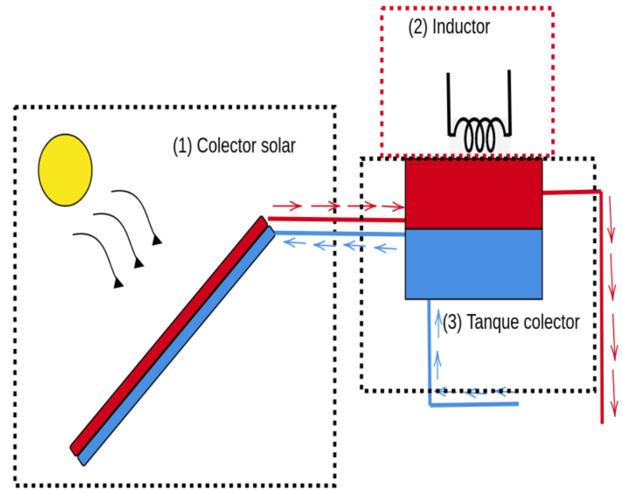

Figure 1. General diagram of the solar heater and inductor system

Starting with the solar collector, the heat energy emission power from the Sun can be estimated by the Stefan-Boltzmann law, given by Eq. 1.

$$E = \sigma * T_e^4 \tag{1}$$

Where E is the emission power given by the units $[\mathrm{W}/\mathrm{m}^2]$, σ is the Stefan-Boltzmann constant with value of $5.6x10^{-8}[W/m^2K^4]$ and is the effective temperature. If Eq. 1 is multiplied by the emission surface of the Sun, given by, $A = 6.09x10^8 m^2$a solar power of $P = 3.77x10^{26}W$ is obtained, the power mentioned above must be used in a certain proportion depending on the design of the solar collector in Figure 1. In this investigation, works with a solar collector with cylindrical geometry.

B. Fundamental equation of a solar heater

To model the behavior of the thermo-fluid, in this case water, the first approximation behaves as an incompressible and non-viscous fluid, which can be described by the Navier-Stokes equations for the conservation of energy (Eq. 2) .

$$\frac{\delta}{\delta t}[\rho(e+\frac{1}{2}v^2)]+\nabla\boldsymbol{.}[\rho(e+\frac{1}{2}v^2)] = -\nabla\boldsymbol{.}\mathbf{q}+\nabla\boldsymbol{.}(\mathbf{q}\boldsymbol{.}\sigma)+\rho\mathbf{V}\boldsymbol{.}\mathbf{F} \tag{2}$$

where ρ is the density of the fluid, e the internal energy, $\boldsymbol{V}$ is the velocity, $\boldsymbol{F}$ is the force, and $\boldsymbol{q}$ is the amount of heat energy. In the production and design standard for solar thermal energy collectors, the cylindrical geometry is used, so that Eq. 2 is transformed to cylindrical symmetry for simplicity of numerical solution, and considering Eq. 2 in terms of temperature of the system, this becomes Eq. 3 (Wannagosit CS-l., 2018).

$$\frac{1}{\alpha}\frac{\delta T}{\delta t} = \frac{\delta^2 T}{\delta r^2} + \frac{1}{r}\frac{\delta T}{\delta r} + \frac{1}{r^2}\frac{\delta^2 T}{\delta \theta^2} + \frac{\delta^2 T}{\delta \theta^2} + \frac{\delta^2 T}{\delta z^2} + \frac{\dot{q}}{k} \quad (3)$$

where α is the thermal diffusivity, $\dot{q}$ the heat energy flux and k is the thermal conductivity. Eq. 2, as already mentioned, represents the fundamental equation of energy in the fluid, however, the complete thermal system of a solar heater is generally characterized by a thermosyphon and a transmission collector, these are described in detail in the sections 2.3 and 2.4.

C. Thermosyphon

The physical phenomenon on which the thermosyphon is based, corresponds to two main thermodynamic states, which are:

1) The cold water is driven by the force of gravity from the container tank to the bottom of the heating tubes, as shown in Figure 2. Due to solar radiation, the water is heated and pushed by the thermal shock to the top of the tank.
2) Since hot water is less dense than cold water, it is always kept in the upper part (see Figure 2), generating thermal shocks of the fluid, maintaining a rotating cycle in the system that distributes the hot water.

In mathematical terms, the thermosyphon can be modeled using Eq. 3, it can be divided into three main sections: evaporation, adiabatic and condensation, which are modeled by Eqs. 4, 5 and 6.

$$T^n_{steam} = \alpha \Delta t \left(\frac{\delta^2 T}{\delta r^2} + \frac{1}{r}\frac{\delta T}{\delta r} + \frac{1}{r^2}\frac{\delta^2 T}{\delta \theta^2} + \frac{\delta^2 T}{\delta \theta^2} + \frac{\delta^2 T}{\delta z^2} \right) + T^{n-1}_{steam} \quad (4)$$

Discretizing Eq. 3 in terms of finite differences, we have that the evaporation temperature of the fluid (Eq. 4) is symbolized on the right by T^n_{steam} and T^{n-1}_{steam} on the left. For the condensation region, the model is given by Eq. 5.

$$T^n_{cond} = T^n_{steam} - \left(\dot{Q}\left(Z_3 + Z_\gamma\right) \right) \quad (5)$$

where $Z_3$and Z_γ are known as thermal resistances and $\dot{Q}$ is the remainder of thermal energy. Finally, Eq. 6 describes the fundamental equation of the thermosyphon.

$$\dot{Q} = i_G A_{avec}\left(\tau_{avec}\alpha_{avec}\right) - \dot{Q}_{avec} - \dot{q_{avec}} A_{fin} \quad (6)$$

where$\dot{Q}$ represents the heat energy in the siphon system, and $\tau_{avec}\alpha_{avec}$ are surface absorption parameters (Wannagosit, Sakulchangsatjatai, Kammuang-lue, & Terdtoon, 2018).

D. Electromagnetic Induction Heating

At present, electromagnetic induction heating applications are low cost, due to the low frequency consumption of electric current (which is around 50 Hz). In general, these systems generate a magnetic field through the circulation of an electric current in a coil, producing heat due to the resistance of said current, this phenomenon is known as the Joule effect.

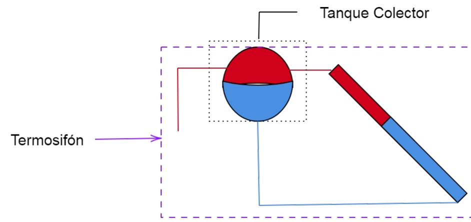

Figure 2. General diagram of the thermosyphon

To model heating by electromagnetic induction, the Ampere equation is used in its quasi-static state, which eliminates the displacement of the electric current, this is described in Eq. 7.

$$\nabla x H = J \quad (7)$$

On the other hand, taking the Faraday equation, dividing it by the equation of the magnetic field and applying the rotational operator to it, we obtain Eq. 8.

$$\nabla x(\frac{1}{\mu}\nabla x E) = -\frac{\delta J}{\delta t} \quad (8)$$

Finally, Eq. 9 fully describes the partial change of the electric field in time, with respect to the partial change of the current in time (Bay, Labbe, Favennec, & Chenot, 2003). Better known as the general equation for electromagnetic induction.

$$\sigma\frac{\delta E}{\delta t} + \nabla x(\frac{1}{\mu}\nabla x E) = -\frac{\delta J_s}{\delta t} \quad (9)$$

To perform the simulation of the solar heater, Eqs. 2 - 9 were implemented in COMSOL Multiphysics, which is a software used for the analysis and resolution of problems in physics and engineering using finite element. The following section details the operation of the algorithms for optimizing the parameters of the electro-thermal models, which in turn communicate with COMSOL Multiphysics to optimize the simulation.

III. Computational optimization

Computational optimization refers to a set of methods that seek to solve a mathematically modeled problem, which is to be optimized, that is, to find its minimum or maximum point, based on the calibration of different parameters. A particular type of computational optimization methods are metaheuristics, which implement strategies that guide a set of candidate solutions (randomly generated) toward an optimum, at best, the global optimum of a cost function, also called objective function, whose variables or parameters to be optimized are in accordance with the domain of the problem. The main task of the objective function is to measure how good a candidate solution is.

Among the most popular metaheuristics are bio-inspired algorithms such as Particle Swarm Optimization, Ant Colony Optimization, as well as evolutionary algorithms such as Genetic Algorithm and Differential Evolution. A particular type of metaheuristics are the Distribution Estimation Algorithms (EDAs).

EDAs build explicit probabilistic models that are iteratively refined to produce better and better solutions for a particular problem. This characteristic allows EDAs the ability to adapt to the structure of the problem to be optimized, reducing its computational cost. In the state of the art, superior performance of EDAs has been reported against algorithms such as Particle Swarm Optimization and Differential Evolution.

Broadly speaking, an EDA consists of the following steps:

1) Generate an initial population.
2) Select a sub-set of individuals with good performance, from the initial population.
3) Build the probabilistic model from this subset.
4) Generate a new population from the probabilistic model.
5) Incorporate the best element (s) from the previous population to the new population.

One of the EDAs that has shown greater efficiency in the face of continuous domain problems is the Symmetric Approximation Energy-based Distribution Estimation algorithm (SEED). This algorithm is the one selected to optimize the problem posed by this research, because no external parameters are required for its operation, only the initial population. In addition, the SEED algorithm is able to find solutions quickly, thus reducing the necessary computational cost. Its operation is detailed below (De Anda-Suárez & Calzada-Ledesma, 2019).

A. *Symmetric-approximation Energy-based Estimation of Distribution*

In recent years, scientists have turned their attention to the Boltzmann probability distribution function (Eq. 10), as it provides several advantages when implemented in EDAs based on in energíto.

$$P_x = P(x;\beta) = \frac{1}{Z}e^{\beta gx} \tag{10}$$

However, various studies in the state of the art report that direct sampling of the Boltzmann function, to update the probabilistic model, is not practical. To solve this, SEED uses an approximation to the Boltzmann function through a Gaussian distribution with parameters μ (Eq. 11) and v (Eq. 12), this through the minimization of the Jeffreys divergence calculated between the Gaussian (Q_x) and Boltzmann (P_x), in order to use that distribution as a probabilistic model.

$$\mu = \frac{\frac{1}{z\beta}\int_x e^{\beta g_x} x dx + \int_x x g_x Q_x dx}{\frac{1}{\beta} + \int_x g_x Q_x dx} \tag{11}$$

$$v = \frac{\frac{1}{z\beta}\int_x e^{\beta g_x}(x-\mu)^2 dx + \int_x g_x (x-\mu)^2 Q_x dx}{\int_x g_x Q_x dx} \tag{12}$$

Unlike other EDAs based on Boltzmann, where the Boltzmann parameter is determined heuristically, SEED is characterized by calculating this value in a self-adaptive way to the problem (De Anda-Suárez & Calzada-Ledesma, 2019).

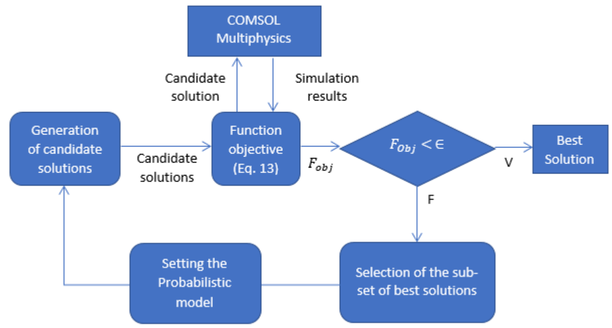

Figure 3. Parameter optimization using SEED

B. *SEED algorithm*

At the beginning of the algorithm, a population of N solutions $P^{(t)}$ is initialized under a uniform distribution and evaluated using an objective function. An individual in the population is denoted as $x_1 = [x_1, \vec{x}_{2,} \ldots, x_n]$ and $g(\vec{x_1})$ for $i = 1, 2, ..., N$, the target values. After the population is evaluated, in order to reduce the computational cost, it is ordered based on $g(\vec{x_1})$, where the first element of the population is the best individual, denoted as $P^{(t)}_{best}$. Subsequently, a sample of the ordered population is selected by means of a truncation, and with this the probabilistic model is built. Then a new population $P^{(t+1)}$ is sampled from a normal distribution with parameters $\mu^{(t)} = [\vec{\mu_1}, ..., \mu_n]$ and $v^{(t)} = [\vec{v_1}, ..., v_n]$ (2 and 3 respectively for each dimension of the vector). In the end, if $P^{(t)}_{best} \geq P^{(t+1)}_{best}$, $P^{(t)}_{best}$ it is incorporated into the new population. The SEED algorithm continues in the convergence cycle until it meets a stop criterion, usually a defined number of iterations or until the desired target value is reached. (De Anda-Suárez & Calzada-Ledesma, 2019).

IV. Optimized Design Using Evolutionary Algorithms

The objective of the evolutionary process is to find the appropriate parameters for the design of the heating tube, the geometry of the collecting tank and finally the design of the inductor. In Figure 3, the general diagram of the methodology for the parameter optimization process is shown.

A. *Methodology*

Below is a detailed description of the optimization process illustrated in Figure 3.

1.- The electro-thermal parameters to optimize for the design of the solar heater and the electromagnetic inductor are established, these are shown in table 1 and table 2.

2.- For this experimentation, the SEED algorithm is configured with an initial population of 50 candidate solutions of dimension 6 (the total of parameters), that is, a population of

Parameter	Description	Domain
L	Tube length	0.5 to 1.5 m
D	Tube diameter	0.05 to 0.1 m
V	Container volume	from 10 to 50 L.

Table I
PARAMETERS FOR SOLAR HEATER.

Parameters	Description	Domain
N	Number of coil turns per layer	10 to 500
L	Length of heat transfer tube	0.01 to 0.2 m
F	Oscillation frecuency	70 to 100kHz

Table II
PARAMETERS FOR ELECTROMAGNETIC INDUCTOR.

Parameter	Description	Domain
L	Container length	1.5 m
D	Container diameter	0.17 cm
V	Container volume	25 L.

Table III
PARAMETER RESULTS FOR SOLAR HEATER.

Parameters	Description	Domain
N	Number of coil turns per layer	125
L	Length of heat transfer tube	0.12 m
F	Oscillation frecuency	75kHz

Table IV
PARAMETER RESULTS FOR ELECTROMAGNETIC INDUCTOR.

"random" parameter configurations, whose efficiency will be measured with the function objective (Eq. 13), this is designed for maximize water temperature and in turn minimize the amount of electrical energy consumed.

$$F(\vec{p},t) = \sum_{t=1}^{12} \{T(t)_{ideal} - [T_{solar}(t,p_1) + T_{inductor}(t,p_2)]\}^2 \tag{13}$$

where $T(t)_{ideal}$ it is the ideal temperature for human consumption, according to the change of seasons in the year, T_{solar} it is the temperature reached by the COMSOL simulation, $T_{inductor}(t)$ while it is the result of the induction system simulation. Finally, p_1 and p_2 are the set of simulation parameters for the heater and inductor respectively, described in Tables 1 and 2.

3.- The calculation of the objective function depends on the results obtained by the simulations in COMSOL Multiphysics, therefore, once the efficiency of each of the candidate solutions of the current population has been measured, the information obtained will be feedback to the algorithm SEED, allowing you to adjust or evolve the probabilistic model (see Section 3.1) to generate a new population of solutions, which will be evaluated again with the objective function.

4.- The evolutionary process is carried out iteratively until the best parameter configuration is found that optimizes the objective function.

5.- As mentioned in Section 3.2, a stop criterion must be established, for this particular case, the evolutionary process will stop if any of the candidate solutions reaches an objective value (F_{obj}) less than a margin of error $\epsilon = 0.005$ or if a total of 50,000 iterations are completed.

6.- The experimentation was carried out on a computer with Linux OS, i7 processor and 16 GB of RAM. The SEED implementation was done in the Java programming language. It should be noted that the graphical simulations in COMSOL Multiphysics, for all the candidate solutions, were not carried out during the evolutionary process, since this would imply a considerable computational cost. In this regard, for illustrative purposes, the coupling model between the solar heater and the electromagnetic inductor is graphically simulated, with the best parameter configuration found by SEED, which is calibrated to maximize the water temperature, minimizing the amount of electrical energy consumed.

V. RESULTS AND DISCUSSION

In this section, the graphic simulation (Figure 4) performed with the parameters found (Tables 3 and 4) by the SEED algorithm is shown. In Figures 4a and 4b, the graphical simulation of the heating tube is shown, which absorbs the heat energy from the Sun. The lightest region represents the hottest area in the tube, whose temperature is above 320 ° K (about 50 ° C), suitable for human consumption. On the other hand, the darkest region represents the coldest zone, in the simulation temperatures below 0 ° C are considered; however, in practice, the temperature in this area will be limited to room temperature. Finally, in Figure 4c, the result of the heat energy transfer zones of the system is shown. Table 3 shows the parameter settings for the container geometry. It can be seen that the use of the electromagnetic inductor allows a reduction in the standard dimensions of the existing containers on the market, whose standard measure is 1.8 m and 25 cm in diameter. The volume of the container designed by the SEED algorithm is 25 L, which is suitable for human use. It should be noted that in practice, adiabatic walls must be added to minimize the loss of heat energy and it must be taken into account that this slightly increases the dimensions of the container.

Finally, in Table 4, the values of the parameters for the inductor are shown. As can be seen, the number of turns per layer of the inductor is 125, this is important, since the copper wire necessary to create the inductor is relatively little compared to standard inductors, allowing to create a low-cost inductor. The length of the heat transfer tube is 0.12 m. Finally, the result for the frequency oscillator is 75 KHz, which allows adjusting to the electronic elements on the market.

VI. CONCLUSIONS

Based on the experimentation carried out, it is concluded that it is possible to carry out the optimized design of a hybrid

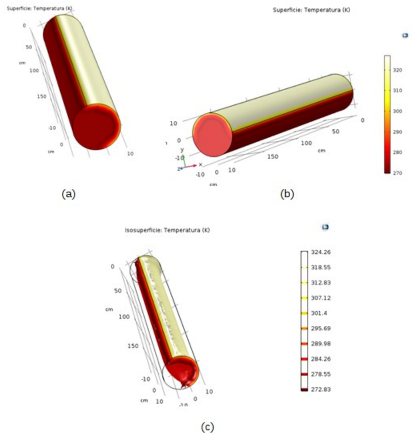

Figure 4. Graphic simulation of the heating tube by transfer of solar energy.

solar / induction heater, obtaining results that allow the real manufacture of said system at a low cost in the future, this due to the optimization carried out by the algorithm SEED.

An essential contribution is the coupling of the SEED algorithm to the physical simulation of COMSOL, through the designed objective function. From what we have investigated in the state of the art, these types of approaches are few, which is why we consider that these applications can be widely exploited in the field of computational physics for the design of thermodynamic systems.

As future work, we intend to carry out the actual manufacturing of the design presented here, adding a system based on artificial intelligence and the Internet of things, to monitor and predict climate change, so that a solar orientation system can be implemented, providing a better user experience.

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