Traveling Wave Induction Heating Control Based on Robust Intelligent Controller

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ABSTRACT
The traveling wave induction heating (TWIH) is the most efficient method for heating flat metals. Since the flat metal is very sensitive to heating temperature, then controlling the temperature is essential to prevent excessive heating and improve performance. This paper proposed an intelligent controller to adjust the workpiece temperature at the desired value. An intelligent Proportional-Integral-Derivative (PID) controller based on Artificial Neural Network (ANN) is proposed and optimized by using particle swarm optimization technique. Results verify the robustness of the proposed intelligent controller as response to any variation of system parameters. Temperature tracking performance gives a very small overshoot and steady state error responses less than 1%, with fast rise time about 1s. The influence of changing strip material, thickness, ambient temperature, or any external disturbance can be overcome due to the control loop. This controller increases the capability of the system to work with different material or multi-thickness strips without needing to change system setting.

KEYWORDS: Traveling wave induction heating, PID based on neural network, Optimum controller, Particle swarm optimization.

INTRODUCTION
The traveling wave induction heating system is a promising technique used in some industrial applications for heating flat metals. There are many efforts in the literature concern to enhance the performance of the TWIH system and improve the heat profile. Al-Shaikhli et al. [1] proposed new configurations of the concentrator yoke of the traveling wave induction heater to reduce the effect of the leakage flux, the proposed configurations improves the efficiency, reduces the input current and focuses the eddy current within the heating region, and hence increases the temperature. Al-Shaikhli et al., [2] proposed a five-phase traveling wave induction heating instead of six-phase system; the proposed heater represents a balance load to the power utility, the same performance of the six-phase system can be obtained by the new system with improving the efficiency and the power factor, besides reducing cost and weight of the heater. Al-Shaikhli et al. [3] proposed a new intelligent model to approach the finite-element solution of the TWIH system. This model is based on artificial neural network which represented three stages of the electromagnetic and thermal processes. The model reduced the computational time with an acceptable error with respect to finite-element solution. Youhua Wang, et al. [4] introduced combination of neural network with a finite element method to predict eddy current distributions on the thin conducting strips. This method is used to predict the initial value of the eddy current distribution that used in the finite-element analysis. Tested examples show quite good accuracy of the prediction, which accelerate the iterative solution process. Junhua Wang, et al. [5] proposed a new design of heater poles by made
distributed vernier in the pole shoes to reduce the slot effect, results show more uniformity of heat distribution. Junhua Wang, et al. [6] proposed a novel TWIH system with distributed windings and magnetic slot wedge (SW-TWIH) to address the inhomogeneous eddy current density problem which dominates the thermal distribution on the surface of work strip. The proposed SW-TWIH enabling the magnetic fluxes generated by each phase to interact and complement with each other so as to generate more uniform and concentrated eddy current density. The good performance of the proposed system has been verified by using FEM simulation. S. L. Ho, et al. [7] proposed a novel crossed traveling wave inductor (C-TWIH) system for heating thin strips. Compared with a typical TWIH device, C-TWIH has more uniform and concentrated eddy current density distributions. This is because the C-TWIH exploits a three-phase induction heater with crossed yoke arrangement, and the magnetic fluxes generated by each phase are interacting and complementing each other to compensate for the weak magnetic areas of each phase. The undesired temperature non-uniformity is reduced by 43% compared with those in typical TWIH devices. Kenneth Frogner, et al. [8] presented a strategy for decoupling the currents in TWIH, based on the anti-series or anti-parallel connection of several inductors. The study investigates the coupling effect in terms of amplitude and phase shift. Measurements indicate that the strategy eliminates the coupling effect, increasing the efficiency, and simplifying control.

In the literature there is absence of any effort of control the workpiece temperature in the TWIH system. Since, the thin metal sheet is very sensitive to temperature then controlling the temperature is very important matter. The difficulty of analysis and solving the TWIH problem is the main obstruction of design and adapt the controller. The intelligent model proposed by Al-Shaikhli et al. [3] gives the ability of designing and adapting a controller of the TWIH.

This paper proposed an intelligent Proportional-Integral-Derivative (PID) controller based on artificial neural networks to control the temperature of the workpiece. The controller is designed by using the intelligent model of the TWIH which proposed in the previous work. The weights of the PID-NN controller are adapted and optimized by using Particle Swarm Optimization technique. The robustness of the proposed controller is demonstrated by different commands tracking. The influences of workpiece thickness and material variation are examined. Furthermore, the effect of the changing of the ambient temperature on the system performance as well as any external disturbance has been investigated for different operation conditions.

Control Algorithms:

In order to properly control a power supply or the produced temperature heating system it is necessary to use a variety of control algorithms. These may be comprised of open and closed loop control systems to accomplish the control of material output power and temperature. This temperature control and its response can be handled in verity of ways that are described below.

Open-loop System (Feedback Control System):

A true open-loop system would run without feedback by simply setting an input variable to fluctuate within an acceptable range without feeding back any indication of magnitude, phase frequency, temperature, and so on. If any disturbance accrue for some reason, the system output will be changed because there is no feedback to automatically adjust the system input to compensate the changes in the output variable.

Many open-loop systems are combinations of closed-loop components that provide a regulated input variable to the system but provide no measurement or feedback of the final critical system output variable. For example, an induction heating power supply may use regulator circuits to provide a very stable input power to the heating coils, whereas no measurement is made of the final exit temperature of the workpiece. In this case the system is running essentially open-loop with the assumption that stable input will provide stable output.

Closed-loop System:

If it is required to obtain the desired output value a feedback closed loop must be implementing. This can be done in the induction heating system by measuring the temperature and adjusting the controller response based the difference between the actual and the desired temperature. This can be achieved by several methods.

ON-OFF Control Algorithm:

The ON-OFF control has two states; it is either fully ON or fully OFF state. If the value of the controlled output variable is below the lower set point the error signal will drive the control to turn fully ON, providing maximum power to the system until the value of the controlled output variable exceeds the upper set point as shown in Figure (1). With this type of control the value of the controlled output variable will oscillate about the desired value, the rate of oscillation depends on the system time constant and the upper and lower set point levels.
PID Controller:

The PID controller involves three separate action parameters: the Proportional, the Integral and the Derivative. These three parameters form the PID calculation. The proportional value determines the reaction to the instant error; the integral value determines the reaction based on the sum of recent errors and the derivative value determines the reaction based on the rate at which the error has been changing. The weighted sum of these three actions is used to adjust the process via a control element such as the power supply of a heating element.

The transfer function of the PID controller is as the following:

\[ K_p + \frac{K_i}{s} + sK_d = \frac{s^2K_d + K_p + K_i}{s} \]  

Where, \( K_p \) is the proportional gain, \( K_i \) is the integral gain and \( K_d \) is the derivative gain.

By tuning these three gains in the PID algorithm, the controller can provide control action designed for specific process requirements. The response of the controller can be described in terms of the responsiveness of the controller to an error, the degree to which the controller overshoots the set point and the degree of system oscillation. It should be noted that the use of the PID algorithm for control does not guarantee optimal control of the system or system stability [9].

Discrete representation of the PID controller:

In the past few decades, analog controllers have often been replaced by digital controllers whose inputs and outputs are defined at discrete time instances. The digital controllers are in the form of digital circuits, digital computers, or microprocessors. The discrete-time PID controller means discretizing the continuous-time to discrete-time. The discrete PID controller can be represented as follow:

Consider the continuous time expression of a PID controller in ideal form:

\[ u(t) = K_p(e(t) + \frac{1}{T_i}\int_0^t e(\tau)d\tau + T_d \frac{d}{dt}e(t)) \]  

Where, \( T_i \) and \( T_d \) are the integral and derivative time constants respectively.

If the sampling time of discretization is \( \Delta t \). Then the integral term above can be considered “discrete” via a trapezoidal approximation:

\[ \int_0^t e(\tau)d\tau \approx \sum_{i=1}^{k} e(t_i)\Delta t \]  

Where, \( e(t_i) \) the error of the discrete time system at the \( i-th \) sampling instant.

Also, the backward-finite difference approximation of the first-order derivative:

\[ f'(t) = \lim_{\Delta t \to 0} \frac{f(t)-f(t-\Delta t)}{\Delta t} \]  

Applying the backward-finite difference approximation to the discrete time derivative term in equation (6.2) becomes:

\[ \frac{d}{dt}e(t_i) \approx \frac{e(t_i)-e(t_{i-1})}{\Delta t} \]  

Thus, the discrete time control law, or “positional algorithm”, becomes,

\[ u(t_k) = K_p(e(k) + \frac{\Delta t}{T_i}\sum_{i=1}^{k} e(t_i) + T_d \frac{e(t_{i})-e(t_{i-1})}{\Delta t}) \]
An “incremental algorithm” or “velocity algorithm” may be obtained by subtracting \( u(t_{k-1}) \) from \( u(t_k) \).

\[
\Delta u(t_k) = u(t_k) - u(t_{k-1})
\]

Where,

\[
\Delta u(t_k) = K_p[e(k) - e(k-1)] + \frac{\Delta t}{T_i} \sum_{i=1}^{k} e(t_{i-1}) - e(t_{k-2}) + T_d \frac{e(t_k) - e(t_{k-1}) - e(t_{k-2})}{\Delta t}
\]  

(7) \( K_p \) and \( T_i \) are the P and I parameters. \( T_d \) is the D parameter.

\[
\Delta u(t_k) = K_p[e(k) - e(k-1)] + \frac{\Delta t}{T_i} \sum_{i=1}^{k} e(t_{i-1}) - e(t_{k-2}) + T_d \frac{e(t_k) - e(t_{k-1}) - e(t_{k-2})}{\Delta t}
\]

(8)

\[
\Delta u(t_k) = K_p[e(k) - e(k-1)] + \frac{\Delta t}{T_i} \sum_{i=1}^{k} e(t_{i-1}) - e(t_{k-2}) + T_d \frac{e(t_k) - e(t_{k-1}) - e(t_{k-2})}{\Delta t}
\]

(9)

Note: \( \sum_{i=1}^{k} e(t_{i-1}) - e(t_{k-2}) = e(t_k) \)

Therefore,

\[
\Delta u(t_k) = K_p[e(k) - e(k-1)] + \frac{\Delta t}{T_i} e(t_k) + \frac{T_d}{\Delta t} (e(t_k) - 2e(t_{k-1}) + e(t_{k-2}))
\]

(10)

With the development of modern computer technology and control theories such as fuzzy and neural networks, neural networks have been extensively used in the areas of finding the control parameters of the PID controller. The PID controller combining a Neural Network controller can tune automatically and modify the robust PID parameters. The PID controller combining BP neural network can give satisfactory results. Figure (2) shows the block diagram of the PID controller based on BP neural network [11].

**Neural Network PID controller:**

The drawback of the PID controller is not suitable for the control of long-time delay and nonlinear systems, in which the tuning of the P, I, and D parameters are difficult [10]. With the development of modern computer technology and control theories such as fuzzy and neural networks, neural networks have been extensively used in the areas of finding the control parameters of the PID controller. The PID controller combining BP neural network can give satisfactory results. Figure (2) shows the block diagram of the PID controller based on BP neural network [11].

**Fig. 2:** The Neural Network based PID controller

The proposed adaptive control law based on neural network technique is as the following:

\[
\text{net}_1(k) = V_1 [e(k) - e(k-1)] + V_2 e(k) + V_3 [e(k) - 2e(k-1) + e(k-2)]
\]

(13)

\[
\text{net}_2(k) = V_4 [e(k) - e(k-1)] + V_5 e(k) + V_6 [e(k) - 2e(k-1) + e(k-2)]
\]

(14)

Where, \( e(k) \), \( e(k-1) \) and \( e(k-2) \) are the input vectors. \( q_1 \) and \( q_2 \) are the neural networks that can be obtained from the activation function “F”:

\[
q_{1,2} = \frac{2}{1 + e^{-2 \text{net}_{1,2}}} - 1
\]

(15)

The control law of the controller action:

\[
u(k) = u(k - 1) + q_1 w_1 + q_2 w_2
\]

(16)

The control parameters of the PID-NN controller are \( V_1 \) - \( V_6 \) and \( W_1, W_2 \) (Ahmed S. Al-Araji, Ahmed I. Abdulkareem, 2012).

In spite of the BP is powerful computational tool that have been used extensively in the areas of finding the correct parameters (weights), it also has the shortcoming that has long training period to meet the desired performance of the controller system. To improve the convergent speed and to prevent the weights getting trapped into local optima, the particle swarm optimization (PSO) algorithm can be adopted to evaluate the PID neural network parameters.
**PID-NN Based on Particle Swarm Optimization:**

The PSO algorithm is an optimization technique that can be applied using multivariable function optimization with many local optimal points, as presented by Kennedy and Eberhart in 1995 [12, 13]. The principle of the PSO algorithm was inspired by observations of natural social behavior, such as bird flocking and fish schooling. The key differences between the PSO and other global optimization approaches were the easy implementation and fast convergence of the former.

Following the aforementioned flocking analogy, PSO modeled several cooperative “bird”, termed particles in this case, acting together in a “flock”, otherwise known as a swarm. Each particle in the swarm has a fitness value mapped by an objective function and an individual velocity, which the particle uses to determine the direction and distance of the movement. Each particle exchanges the information obtained through its respective search processes [13]. The position of a particle is influenced by two variables: the best solution found by the particle itself (pbest), which is stored for use as individual best position, and the best particle in the neighborhood (gbest), which is stored as the best global position for the swarm. The particle swarm uses this method to move towards the best position, continuously revising its direction and velocity as needed; following this approach, each particle ultimately moves toward an optimal point or close to a global optimum [13]. The standard PSO method can be defined according to the following equations:

\[ v_i(k + 1) = Wv_i(k) + C_1R_1(p_{best} - x_i(k)) + C_2R_2(g_{best} - x_i(k)) \]  
\[ x_i(k + 1) = x_i(k) + v_i(k + 1) \]  
\[ i = 1, 2, \ldots, n \]  

Where \( x_i \) and \( v_i \) are position and velocity of particle \( i \), respectively, \( k \) represents the iteration number, \( W \) is the inertia weight, \( R_1 \) and \( R_2 \) are random variables whose values are uniformly distributed in the range \([0 \rightarrow 1]\), and \( C_1 \) and \( C_2 \) represent the cognitive and social coefficients, respectively. \( p_{best,i} \) is the individual best position of particle \( i \), and \( g_{best,i} \) is the best global position of all the particles in the swarm. \( n \) is the number of birds (particles). If the initialization condition (19) is satisfied, the method is updated according to (20):

\[ f(x_{ik}) > f(p_{best,i}) \]  
\[ p_{best,i} = x_{ik} \]  

Where; \( f \) represents the objective function that should be maximized.

In this work the PSO algorithm is used to evaluate the optimum values of the PID-NN controller weights instead of applied the traditional BP method as shown in Figure (3).

![Fig. 3: The Block Diagram of the Optimized PID-NN Controller](image)

A MATLAB program is developed to find the optimal values of the controller parameters \( V_1-V_6 \) and \( W_1, W_2 \). The integral time square error (ITSE) is used as objective fitness function of the system performance, a minimization algorithm is applied in the search domain of the particles position and velocity.

\[ ITSE = \int e^2 dt \]  
\[ ITSE = \int e(k)^2 dt \]  
\[ ITSE = \int e(k-1)^2 dt \]  
\[ ITSE = \int e(k-2)^2 dt \]  

The flowchart of the PSO algorithm is illustrated in Figure (4).

**System Performance:**

As mentioned before the TWIH system has no single mathematical model and the problem can be solved numerically for specific case. Therefore, in order to design the suitable controller and adjusting the controller parameters it’s required to employ suitable model including the electromagnetic and thermal processes. The proposed intelligent model can be used efficiently in this work to design and optimize the controller parameters. The performance of the optimization algorithm, by using the optimizing coefficients \( C_1=C_2=1.49 \) and \( W=0.73 \), gives the optimum values of the PID-NN controller in 100 iteration as the following: \( V_1=1.698, V_2=0.8997, \)
$V_1 = -2.914, V_2 = 3.218, V_3 = 2.993, V_4 = 0.607, W_1 = 117.825, W_2 = 117.825$. It’s important to emphasize that the control signal (system input) is the supplied voltage and ranged from 0 to 350V and limited within this range. The optimization performances are shown in Figure (5).

![Flowchart of the PSO Algorithm](image)

**Fig. 4:** The Flowchart of the PSO Algorithm
The performance of the TWIH system tracking different desired temperature is shown in Figure (6) for aluminum workpiece of 15mm thickness and 25°C ambient temperature. Result shows an excellent tracking performance with zero overshoot and steady state error with reducing of heating time.

**Fig. 6:** Tracking Performance for Different Commands
The robustness of the proposed PID-NN controller can be verified by changing the heated workpiece parameters such as: thickness, material type (conductivity), changing the ambient temperature, or changing in the temperature profile caused by any external disturbance. Figure (7) show the responses of the system under the action of changing thickness of the strip from 15 to 5mm at time 5 s, it can be seen that the controller success to overcome the effect of this change. Figure (8) shows the performance of the control loop under the changing of material type from lead to copper (the conductivity changes from $0.5 \times 10^7$ to $5.8 \times 10^7$). Figure (9) shows the performance of the system when the ambient temperature is falls from 25 to 5 °C. Moreover, Figure (10) shows the temperature performance under reduction of the strip temperature by 50 °C caused by an external disturbance. Obviously, results prove that the proposed intelligent PID controller gives high degree of robustness, which can overcome any kind of changing in material parameters.
Fig. 10: The Performance of External Disturbance

Conclusions:
This paper proposes an intelligent PID controller based on ANN and optimized by using PSO method to adjust the workpiece temperature. The intelligent model is used efficiently to adapt and optimize the PID-NN controller, which is very difficult operation with FEA. Results verify the robustness of the proposed intelligent controller as response to any variation of system parameters. Temperature tracking performance gives a very small overshoot and steady state error responses less than 1% for each, with fast rise time about 1s. The influence of changing strip material, thickness, ambient temperature, or any external disturbance can be overcome due to the control loop. This controller increases the capability of the system to work with different material or multi-thickness strips without needing to change system setting. Furthermore, this controller gives exactly the required temperature to prevent excessive heating the strip.

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