

TEMPERATURE DISTRIBUTION AND PREDICTION OF THERMAL CONDUCTIVITY

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Abstract:

Various limits impact Thermal conductivity of Nano fluid; regardless, some of them are all the more remarkable, for instance, temperature, size and sort of Nano particles and volumetric concentration. In this survey, fake cerebrum network as well as least square assist vector with machining (LSSVM) is applied to predict warm conductivity extent of alumina/water Nano fluid as a component of particle size, temperature and volumetric obsession. LSSVM, Self-Organizing Map and Levenberg-Marquardt Back Propagation estimations are applied to predict warm conductivity extent. Gained results showed that these computations are reasonable instrument for warm conductivity extent figure. The association coefficient values are altogether great and for warm conductivity it is possible to control their strong warm conductivity through picking the part materials and arranging the design. Thus, a PC system that can help an organizer with finding the ideal game plan of materials and development is imperative. In this work, we have cultivated a quick and light-weight warm conductivity evaluation engine, basing on coherent game plans of convincing warm conductivity of composites. A heap of assessment modules connecting with the logical solutions for different plan models is made In this survey, one more methodology considering the local course of action speculation has been made to expect warm conductivity, convective power move coefficient, and thickness of Nano fluids. The non-irregular two liquid (NRTL) model is used hence. The effects of temperature and particle volume obsession with warm conductivity, convective power move coefficient, and consistency are explored. The mobile limits of the NRTL model were gained by fitting with test data.

Introduction:

In generally physical and substance processes, heat move and temperature change occur. Thusly, warm conductivity, a key property that governs a material's direct in power and temperature moving cycles, ought to be thought of, when the material's relevance is surveyed, especially for materials used as electronic devices, space materials, energy materials, etc. For composites, it has been found that the strong warm conductivity depends upon the warm conductivity, volume part and numerical scattering of each and every part. Thusly, controlling the convincing warm conductivity of a composite through picking the parts and it is possible to design the construction. To help an originator with finding the ideal course of action, a PC

structure that can predict the warm conductivity of an arranged composite; show the tendency of warm conductivity changing with the distinction in safeguarded limits; store plentiful information of contender materials, is fundamental. In this work, we have cultivated a warm conductivity assumption system, which is featured by a quick and light-weight calculation engine, and with ability to store and give enormous proportion of materials information. Nanofluids, which are suspensions of nanoparticles in a base fluid, have been found to give a huge force move redesign conversely, with standard fluids like water and ethylene glycol. Disregarding their promising component, there are just barely any distributed outcomes on Nano fluids.

Literature Review:

Nano innovation have been used in a few applications to work on their presentation. For example, by applying nano innovation it is feasible to diminish size of frameworks or further develop strength of materials. A few examinations have been directed on utilization of Nano innovation in heat move applications. One of the main uses of Nano innovation in heat move is usage of Nano fluids. Nano fluids are gotten by scattering of Nano particles into a base liquid. Two techniques are presented for advancement of Nano fluids: one-step strategy which joined Nano particles blend and its scattering in the base liquid, and two-step strategy in which amalgamation and scattering of Nano particles are performed independently. Nano liquids can be used in heat move gadgets, for example, heat lines and intensity siphons to work on their effectiveness and intensity move limit.

Warm conductivity of Nano fluids relies upon referenced boundaries; not with standing, temperature of Nano fluid, molecule size and focus have more massive impacts for a particular Nano molecule type. The reliance of warm conductivity on temperature is ascribed to Brownian movement and decrease of molecule agglomeration by expanding temperature. Furthermore, by expanding temperature, the consistency diminishes which prompts upgrade in Brownian movement. In any case, at high temperature, improvement in warm conductivity can perish because of expansion in interfacial warm protections. One more significant boundary in warm conductivity of Nano fluids, is molecule size. Molecule size of Nano fluids influences Brownian movement and surface impact subsequently, size of Nano particles assumes compelling part in warm way of behaving of Nano fluids. Centralization of Nano molecule in the base liquid is one more viable element for warm conductivity. For example, Wang et al. noticed 36% increment in warm conductivity of liquid by adding 1.36 vol% of graphite into oil. The vast majority of the examinations inferred that the warm conductivity of Nano fluids improve by expanding grouping of Nano particles nonetheless, at high focus the chance of agglomeration increments which makes them unseemly for usages.

A few models have been proposed to foresee thermo physical properties of Nano fluids. Among the different methodologies, ANNs with different calculations showed that they are suitable strategies for anticipating properties unequivocally. Hemmat Esfe et al. proposed an ANN model to foresee dynamic thickness of water based TiO₂ Nano fluid. The

contributions for the proposed model were temperature and fixation. Gotten results demonstrated that the proposed model had the option to assess the unique thickness exactly. Notwithstanding temperature and focus, the shear rate is a persuasive boundary on powerful thickness of Nano fluid which is utilized as info variable in certain examinations. For example, Nadooshan et al applied counterfeit brain network to survey dynamic consistency of SiO MWCNTs 2/10W40 motor oil. The contributions for the applied model were volumetric grouping of Nano particles, temperature and shear rate. In another review, a model was proposed to decide warm conductivity of CuO-SWCNTs/EGwater by utilizing ANN and the outcomes were contrasted and a proposed relationship. The considered contributions for the proposed model were temperature and focus. Results showed that ANN was better for anticipating warm conductivity of the nanofluid contrasted and the relationship. Hemmat Esfe et al. proposed a connection and ANN model to gauge warm conductivity of SWCNT-A Al_2O_3 /ethylene glycol. Temperature and volumetric focus were considered as information factors for assessment. Besides, a review was led on applying ANN for demonstrating warm conductivity of ZnOMWCNT/EG-water by thinking about focus and temperature as information sources. ANN is used for demonstrating warm conductivity of other Nano fluids like ZnO-DWCNT/EG half and half Nano fluid. In view of writing survey, the majority of the led examinations applied ANN for assessing the warm conductivity, thought about temperature and fixation as info factors.

In this review, counterfeit brain network with two different calculations are applied to anticipate warm conductivity of Al_2O_3 water Nano fluid. To display warm conductivity of Nano fluid, its reliance on temperature, size and fixations are considered for Al_2O_3 nanoparticles scattered in water as base liquid.

Classical atomic Monte Carlo (MC) and subatomic elements (MD) reproductions additionally are valuable in clarifying the basics of Nano fluids. As surveys show, MC reenactment has been applied in the investigation of Nano fluids. The earliest such work lead to the significant perception that the power per unit region between two surfaces restricting a straightforward liquid wavers among fascination and repugnance in a rotting way with a period equivalent to the size of the liquid particle prior to arriving at the mass strain at 5-6 sub-atomic breadths. This finding, which traditional continuum hypotheses don't foresee, was hence affirmed tentatively a couple of years after the fact by Horn and Israelachvili utilizing their now well known surface power contraction.

The vast majority of the nanofluid concentrates on revealed in the writing have finished up or accepted that nanofluids give heat move improvement regard to their particular base liquids. Regardless, the evaluation of what comprises an upgrade has still up in the air on a similar premise. An expanded intensity move coefficient may essentially mirror the progressions in the warm actual properties of the nanofluid being tried while the models and relationships created for basic liquids actually apply. For instance, a new report estimated the convective intensity move and strain misfortune conduct TiO_2 water nanofluids in completely evolved laminar and tempestuous streams. The outcomes demonstrated that the tempestuous intensity

move and strain misfortune can be anticipated by the conventional relationships and models, as long as the deliberate temperature-and stacking subordinate nanofluid properties are utilized in working out the dimensionless numbers In the current review, neighbourhood piece hypothesis (LCT) is utilized to anticipate the warm conductivity coefficient, thickness, and convective intensity move coefficient of nanofluids. The impacts of temperature and molecule volume focus have been examined. Aftereffects of this hypothesis have additionally been contrasted and exploratory information and traditional models. At long last, another equation for ascertaining convective intensity move coefficient of nanofluids is presented.

Thermal Conductivity and Evaluation Methods:

The warm conductivity of a composite still up in the air by settling the power conduction condition and where k is the warm conductivity, q is the static force movement and T is the temperature. There are two techniques for settling this issue, numerical procedure and logical system.

For all intents and purposes all of the item things for settling heat move issue rely upon numerical procedure like restricted contrast methodology (FDM) and restricted part strategy (FEM). A numerical procedure bases on looking at the force move and temperature spread inside a specific composite. On the off chance that any distinction in the constitution, for instance, volume part or computation of a section, happens, the game plan becomes invalid. In any case, it is seriously intended to use a numerical system to focus on how the warm conductivity changes with the distinction in constitution, because the preparation and separating for each composite cost long time. Moreover, on the off chance that we want to deal with a composite where the dispersing stage are randomly spread, the handling unpredictability of numerical assessment could end up being incredibly high, which even makes this method impossible. Starting from Maxwell¹ and Rayleigh² various speculative studies^{3,10} have been done to logically decide the issue of conduction in heterogeneous materials. The law of mixes, convincing medium theory^{3,6} and indistinguishable thought method^{7,8} have been extensively taken on as fruitful techniques for warm conductivity evaluation for composites.¹¹ A logical game plan is normally closed basing on one development model, which conventionally consolidates a few improvements, for example expecting the shape and size of scatterings are something basically the same, and the spread is uniform. A savvy course of action can be applied to any composite given that the plan model is significant. For example, a model of round scatterings will keep real despite the compass and thickness of the dissipating.

The fundamental plan models of composites are shown in Fig. 1. Generally, they can be isolated into two classes: overlay composite and dissipating composite. For dispersing composites, as demonstrated by the course of dissipating, they can be detached into three sorts: one layered (1D) heading, two layered (2D) heading and three layered (3D) bearing. The math of a dispersing can be generally tended to by an ellipsoid with semi axes of a , b and c , as shown in Fig.

1. The heading of a not entirely settled by two and ' as shown in Fig. 2. As shown by the most limit and least potential gains of and ', we could conclude which type the dispersing composite is.

Fig. 1 Construction models of composites (a) overlay composite (b) scattering composite with 1D direction (c) scattering composite with 2D direction (d) scattering composite with 3D direction

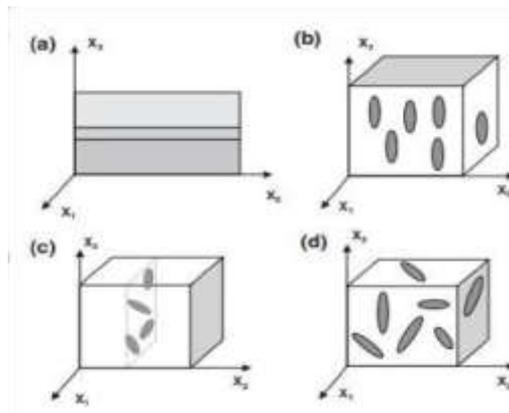
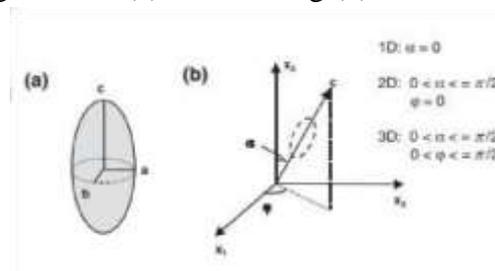


Fig. 2 Math (a) and heading (b) of a scattering



The enlisting multifaceted nature of warm conductivity calculation considering logical plans is a great deal of lower than that of numerical assessment, so it costs essentially less time. For business programming of numerical examination, it regularly expects 20 to 30 minutes or significantly longer to settle the power conduction condition, and a while later another cycle finding out the warm conductivity is significant. While with this system, the calculation of warm conductivity should be possible in 1 second or less.

Materials Data Base:

A materials Data Base has been worked inside this structure, which can store copious information of materials. It is valuable for clients to find legitimate materials when plan a composite, and outfit the evaluation engine with the data anticipated in calculation, as warm conductivity of parts. The outcome records of the appraisal engine can similarly be saved in the informational index, so the data on composite arrangement can be accumulated, and shared and reused by various clients.

Local Composition theory for Nano Fluids Properties:

Nanofluid is a suspension of nanoparticles in a base fluid. Taking into account the differentiation in intermolecular powers, nanofluids can be considered as a non-irregular mix, where the fluid property can be conveyed to the extent that area rather than overall union. Along these lines, the close by course of action speculation can be used for nanofluids. Transport properties of nanofluids, for instance, warm conductivity, convective power move coefficient, and consistency, connect with association of particles. Consequently, these properties of nanofluids not entirely settled by the local piece speculation, which relies upon nonrandom mix and intermolecular powers.

Two Liquid Theory sub-atomic powers. Two Liquid Theory. The two fluid speculation includes two fluids as references. This theory gives a supportive take-off guide for deriving semi-observational circumstances toward address, for example, thermodynamic capacities for mixes. In an equal mix as shown in Fig. 1, each iota is solidly surrounded by various particles, which is implied the brief district around any central molecule as that molecule's cell. In an equal blend of parts 1 and 2, there are two kinds of cells: One sort contains molecule 1 at its center and the other contains particle 2 at its center.

Thermal Conductivity

NRTL model can be utilized for fluid blend warm conductivity. In these situations, J is supplanted by warm conductivity of fluid blend (k) and volume part (s) are taken on rather than mole division.

Shear Viscosity Model

A perceptive neighborhood union speculation for nanofluid shear thickness has been made considering the Eyring and NRTL close by association models. For this item, Eyring's theory for shear consistency has been applied to nonideal blends. Then, at that point, a condition is introduced for shear thickness, which is committed to out of a responsibility in light of non-irregular mixing on the close by level and another fiery piece associated with the strength of intermolecular powers stifling particles from removal from their most ideal congruity positions in the blends.

Convective Heat Transfer Coefficient Model

NRTL model can be used for the liquid blend convective power move coefficient. In these circumstances, J is displaced by convective power move coefficient of liquid mix (h) volume division are embraced as opposed to mole part, and convective force move coefficient for a two section mix can be imparted as under.

$$h = \phi_1 \phi_2 \left(\frac{A_{21} G_{21}}{\phi_1 + \phi_2 G_{21}} + \frac{A_{12} G_{12}}{\phi_2 + \phi_1 G_{12}} \right) + \phi_1 h_1 + \phi_2 h_2$$

Here the convective power move coefficient of not entirely settled by the close by piece

speculation directly. As another procedure for figuring the convective power move coefficient, first, the warm conductivity and consistency of the not entirely set in stone by the close by association speculation. With having two referred to properties, the Reynolds number (Re) and Prandtl number not entirely settled. Then, the Nusselt number is gotten. Generally, the Nusselt number is associated with the Reynolds number and the Prandtl number described as Pr . Overall, the Nusselt number Nu of a nanofluid may be conveyed as follows.

$$Nu_{nf} = f\left(Re, Pr, \frac{k_p}{k_f}, \frac{(\rho C_p)_p}{(\rho C_p)_f}, \phi, \text{ dimensions and shape of particles} \right)$$

In this study, the following formula is proposed to correlate the experimental data for the nanofluid

$$Nu_{nf} = c_1(1 + c_2 \phi^{m_1} Pe_p^{m_2}) Re_{nf}^{m_3} Pr_{nf}^{0.4}$$

Differentiated and the power move relationship for customary single-stage stream, the volume part of suspended nanoparticles and the Peclet number are related with the above explanation. The Peclet number (Pe) depicts the effect of warm dissipating, which is achieved by miniature convective and miniature dissemination of the suspended nanoparticles. The case $c_2 = 0$ insinuates zero warm dissipating, which looks at to the pure base fluid. The atom Peclet number Pe_p in given Eq. is portrayed as

$$Pe = \frac{ud_p}{\alpha_{nf}}$$

where α_{nf} is defined as

$$\alpha_{nf} = \frac{k_{nf}}{(\rho C_p)_{nf}} = \frac{k_{nf}}{(1 - \phi)(\rho C_p)_f + \phi(\rho C_p)_p}$$

With computing the Nusselt number by given Eq. the convective intensity move coefficient of nanofluid is gotten by the accompanying condition.

$$Nu(x) = h(x)D/k_f$$

where D is the cylinder internal width. In the above conditions, the thickness of nanofluid is determined by the accompanying conditions.

$$\rho_{nf} = (1 - \phi)\rho_f + \phi\rho_p$$

The local association based model was applied to ascertain the warm conductivity, consistency, and convective force move coefficient of nanofluids. Exploratory data for these properties for suspensions of Al₂O₃, CuO, TiO₂, Au, Ni, Cu, and SiO₂ nanoparticles in water base fluid and suspensions of TiO₂ and Al nanoparticles in ethylene glycol base fluid are given. To assess the adaptable limits of the NRTL model i.e., (A12, A21, B12 , B 1and B 1), exploratory information should be fitted to relating conditions for warm conductivity, consistency, and convective intensity move coefficient, separately. The nonlinear relapse strategy was utilized for fitting mathematical qualities and trial information and tracking down the NRTL boundaries

Methodologies for Thermal conductivity ratio prediction of Al₂O₃

To get relative warm conductivity of Al₂O₃/water warm conductivity as a component of volumetric obsession, temperature of nanofluid, and size of Nano particles, two cerebrum networks estimations and least square assist vector with machining (LSSVM) are applied which are gotten a handle on immediately in this fragment.

Self-organizing map (SOM)

Self-organizing guides (SOM) are a mind network which was introduced by Kohonen. It isn't normal to set up the association with expected yield during getting ready procedure. In this estimation, the applied association is puts with social events of planning data together to gathering of request them. A SOM structure is arranged considering a 2-layered grid. Neurons affiliations rely upon topological relationship of the applied development. A couple of geologies can be used; regardless, hexagonal and rectangular are the most notable ones. . In SOM, all of neuron has a weight vector which is layered portrayed as $w = (w_{i1}, w_{i2}, \dots \dots, w_{id})$ where $i = \dots 1, 2, \dots \dots, m$ with same aspect as the info space. The calculation is performed in view of following advances.

1. Initializing the 'wis of the $m \times n$ neurons,
2. Finding the best (victor) neuron in light of the underneath Eq. :

$$c = \arg(\min\{\|w_i(t) - x(t)\|\})$$

In the above condition, $x(t)$ and $w_i(t)$ are the information and weight vector of i th neuron at the t th emphasis, separately.

3. Updating the weight vector of neurons by applying Eq $W_i(t + 1) = w_i(t) + h_{c,i}(t)[x(t) - w_i(t)]$ In the above equation, $h_{c,i}(t)$ is a Gaussian neighborhood function defined as:

$$h_{c,i}(t) = \alpha(t) \cdot \exp\left(-\frac{\|r_c - r_i\|^2}{2\sigma^2(t)}\right)$$

In the above condition, $\alpha(t)$ is the learning rate. r and $\sigma(t)$ are the direction position of neuron on the applied guide and width of neighborhood span, respectively. $\alpha(t)$ and $\sigma(t)$ diminish with monotonic pattern as addressed in Eq

$$\alpha(t) = \alpha(0) \cdot \left(\frac{\alpha(T)}{\alpha(0)}\right)^{t/T} \text{ and } \sigma(t) = \sigma(0) \cdot \left(\frac{\sigma(T)}{\sigma(0)}\right)^{t/T}$$

T is the training length.

4. Steps 2–4 are repeated for all the input data.

Levenberg-Marquardt back propagation (LM-BP)

- Another applied computation in this study is Levenberg-Marquardt Back spread (LM-BP). Back inducing (BP) networks are utilized to see plans. A BP network have one or different mystery layers and one data and an outcome layer. Number of neurons in the data layer depends upon the amount of components. Number of centers stealthily layer is described considering the specific condition.
- This model is improved to have higher mixing rate and capability by utilizing the

Levenberg-Marquardt (LM) computation. This estimation (LM-BP) has higher speed in network planning and is more exact in assessment with BP association. The arrangement of this estimation can be summarized as.

- Setting mistake ϵ and introducing weighted coefficients.
- Calculating error index function by applying below Eq

$$E(w^k) = \frac{1}{2} \sum_{i=1}^p e_i^2(w^k)$$

Where p is number of tests. $e_i(w)$ and w_k are mistake of every neuron and weighted coefficient of K th emphasis

Least square support vector machine (LSSVM)

The LSSVM's technique for nonlinear ability gauge is presented as follows. To create the model, a readiness educational still hanging out there. The educational not completely settled as: $\{x_k, y_k\}$

, $k = 1, 2, \dots, N$, where $x_k \in \mathbb{R}^n$ is the i th input data in the data space, $y_k \in \mathbb{R}$ is the value of result related with a foreordained data variable (for instance x_k) and N shows the amount of the planning significant snippets of data. The given wellsprings of data x_k addresses volumetric obsession, nanofluid' temperature, and nano particles' size and result y show relative warm conductivity of Al_2O_3 /water warm conductivity. With the help of (ϕ) the nonlinear capacity, that maps the readiness set in the data space to the high layered space, the backslide perspective of underneath Eq. is made.

$$y = \omega^T \cdot \phi(x) + b \text{ with } \omega \in \mathbb{R}^n, b \in \mathbb{R}, \phi(\cdot) \in \mathbb{R}^n \rightarrow$$

" n " addresses the part of data space, and " nh " conveys the component In which w shows the vector of weight and b imparts a term of inclination. Similarly, the superscript of the unidentified brand name space. A unique improvement issue is achieved, while the LSSVM model is applied. The high level model has to do with the improvement issues as given by under Eq.

$$\left(\frac{\min}{\omega, b, e} \right) \mathcal{J}(\omega, e) = \frac{1}{2} \omega^T \omega + \frac{1}{2} \gamma \sum_{k=1}^N e_k^2$$

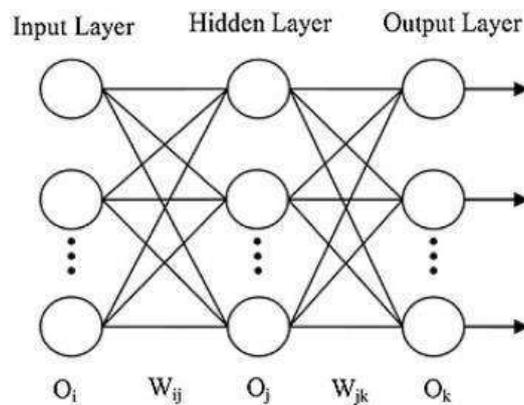
This Eq. is dependent upon the balance requirement shown by the accompanying articulation:

$$y_k = \omega^T \phi(x_k) + b + e_k \quad k = 1, 2, \dots, N$$

in which, γ is the regularization limit, which changes the unpredictability of the model and the readiness bumble and e_k addresses the backslide botch.

To decide the reaction to the restricted smoothing out puzzle, the Lagrangian is worked as shown under.

Fig. 3. Schematic of BP network



Genetic algorithm (GA)

A stochastic method for managing tackle issues associated with upgrade is suggested GA. It relies upon the Darwinian advancement hypothesis and different hereditary heads. These inherited heads contain change.

Fig. 4. The formation of the neurons used and the number of data assigned.

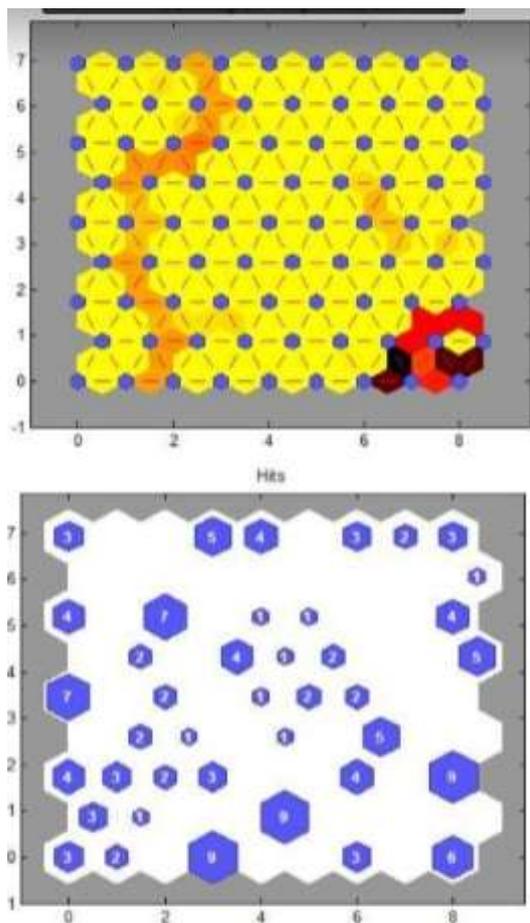
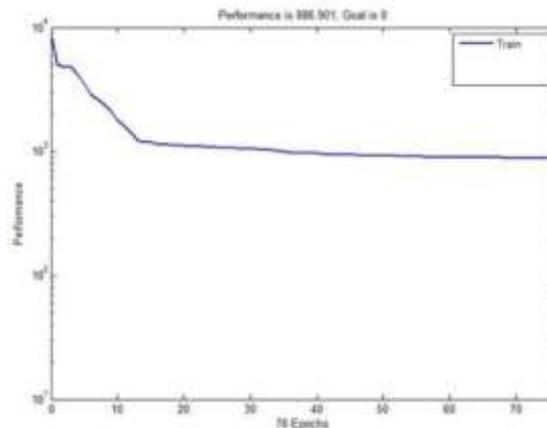


Fig. 5 qa. The general exhibition of the organization carried out for warm conductivity proportion coefficients information.



what's more, hybrid. A confident quality of GAs is that they shouldn't mess around with the stunning capacities' isolating. The stochastic nature related with dynamic evaluation of the health capacity drives it to be a convincing inconsistent web search device. This computation is a preferable choice over subordinate based estimations, since the health capacity can be non-differentiable, stochastic and potentially significantly nonlinear.

Conclusion

A warm conductivity assumption system for composites has been made considering logical plans of power conduction conditions for heterogeneous materials. The system is featured by a high speed and light-weight calculation engine, and an understood materials data base.

Our future work incorporates encouraging an electronic UI for materials decision and development plan, and making this system open from the web, with the objective that it might be used as a supportive and effective decision help gadget for plan of composites.

In this audit, three special connectionist techniques including GALSSVM and counterfeit cerebrum network computations are applied to expect relative warm conductivity of Al₂O₃/water nanofluid. GALSSVM, SOM and LM-BP cerebrum networks have been utilized. Results demonstrated that the referenced calculations are proper to anticipate warm conductivity proportion of nanofluid.

In this review, apparently interestingly, the nearby organization hypothesis has been utilized to foresee warm conductivity, thickness, and convective intensity move coefficient of nanofluids. The consequences of this hypothesis for ascertaining the referenced properties of

Al₂O₃/wate CuO/water, Cu/water

r, ,
SiO₂/water, Ni/water, Au/wate

r,

TiO₂/water, TiO₂/EG, and Al/EG nanofluids are in extraordinary simultaneousness with the preliminary data. The results show that Maxwell's condition misconstrues nanofluid warm conductivity. The assessment of results of the local creation speculation with the preliminary

data yields an AAD of 1.51% for warm conductivity, while the relationship of the customary models with the exploratory data yields an AAD of 42%. The AAD for convective power move was 2.13%. A decently wide recipe for figuring the convective power move coefficient of nanofluid is introduced. The results of this new recipe are in extraordinary simultaneousness with exploratory data. Finally, the understanding between the results of this work with exploratory data underwrites the local combination speculation as one more supportive technique for processing warm conductivity, thickness, and convective power move coefficient of nanofluids conversely, with various models.

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