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RESEARCH ARTICLE

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COMPARISON OF CONTROLLER PERFORMANCE FOR THE ANALYSIS OF SUPERFICIAL CANCER THERAPY

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ABSTRACT

The primary objective of the research work presented is to design a thermal dose controller for hyperthermia treatment using several soft computing techniques, perform simulation studies on the mathematical model of the carcinogenic tissue and compare the controller performance. The non-linear relationship between temperature and dosage, after effects of treatment and constraints on normal tissue protection makes design of thermal dose controller a challenging task. Intelligent control of thermal dose using soft computing techniques like Fuzzy Logic Controller (FLC) and Fuzzy Adaptive Learning Control Network (FALCON) has been simulated on the tissue model and the performance of the controllers are compared in terms of accuracy of output and patient comfort. In the proposed system, optimum thermal dose to which the carcinogenic tissue can be exposed is determined. State space representation of the thermal model of the tissue is used for simulation studies. The performance metrics are the transient response characteristics like rise time, settling time and mean square error. These characteristics are compared to assess the controller performance. The FLC and FALCON performance for both linear and exponential parametrization has been compared. It has been observed that implementation of Fuzzy Controller and FALCON for thermal dose is successful in minimizing the treatment time. Model validation has been done by observing the mean square error which is well within the permissible limits.
The concept of Automatic thermal dose controller has been enhanced using hybrid Neuro-fuzzy Controller (FALCON). The developed controller is applicable for a wide range of thermal therapies like thermal ablation and thermal radiotherapy.

ARTICLE HISTORY

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KEYWORDS

Hyperthermia, Cancer, Fuzzy Logic Controller, Neuro Fuzzy, Thermal dosage

INTRODUCTION

Hyperthermia therapy deals with the utilization of extremely high temperatures for treatment. Depending on the tumor location, there are several approaches to local hyperthermia. Ultrasound hyperthermia has been considered in this research work.
When the ultrasound wave penetrates the human tissue, the wave energy is partially absorbed and transforms into heat energy. The main goal of the ultrasound transducer is to destroy the tumors by exposing them to high intensity, highly focused ultrasound waves. The ultrasound signals generated by the sensor is focused on the tissue that results in the heating of the tissue as shown in Fig.1. The primary reason for using ultrasound technology is that it is non-invasive and also permits a high degree of spatial and dynamic control of heating as compared to the other methods. The limitations of the technique is that it takes longer time to treat large tumors because healthy tissues lying in between the tumor and the

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ultrasound transducer must be allowed to cool in order to avoid inadvertent and undesired thermal damage to the normal tissue. Hence, advanced optimization and control techniques are being proposed and adopted in order to decrease the treatment time for large tumors. This is accomplished by accurate control of the temperature in the cancerous tissue as well as normal tissue.

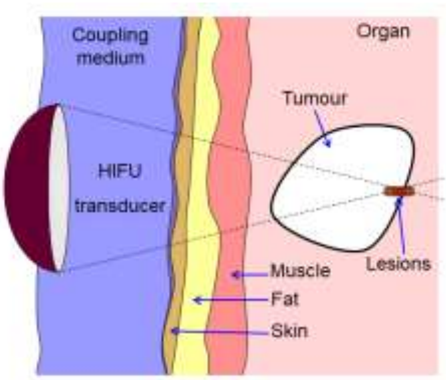

Figure 1. Ultra Sound Hyperthermia Technique

An Artificial Neural Network (ANN) mimics the learning and adaptation ability of the human brain whereas the Fuzzy Logic Technique is based on the human reasoning ability. These are powerful soft computing techniques that have been widely used for various classification, pattern recognition and control applications. A synergistic integration of these techniques results in an efficient hybrid algorithm with improved performance. In the proposed work, ANNs have been used to tune the fuzzy membership functions in order to effectively control the highly non-linear thermal dosage control system.

Diagnostic and therapeutic techniques for carcinogenic tissues has remained a prominent topic of research for many years. Numerous researchers have contributed various techniques and methods for cancer diagnosis and treatment. The seven phase trials that demonstrate the positive effects of small intensity heat therapy techniques are used along with radiation therapy and chemotherapy.[1,2]. Similarly, the utility of high-intensity thermal therapies to coagulate targets distributed in the patient's body in a non-invasive manner has been discussed in various papers. The usage of MR guided ultrasound surgery to thicken the soft breast fibroadenomas in a non- invasive manner is discussed.[3]

Recently, numerous multiple element hyperthermia applications have been developed to be used for larger surface areas. [4].The major drawback that has limited the widespread application of this approach is the need for stable, but homogeneous temperature profile across large treatment surfaces.[5]. Due to the disadvantages of manually powered control techniques, automatic control systems based on temperature feedback from tissue under each independently powered heat source has been attempted [6], using scanned – focused and phased array ultra sound techniques as well as high temperature hyperthermia[7, 8]. Wide range of control techniques like PID, Model Predictive Control have been discussed in literature [9]. Control approaches based on recursive algorithms have been developed. These controllers are found to have high accuracy as well as a high speed of response.[10]

Development of a Fuzzy Controller that is capable of learning and adjusting its characteristics based on neural network learning rules is discussed by Berenji[11] . The use of Genetic Algorithms to tune the Fuzzy parameters in discusses [12]. Farag et al [13] proposed a neuro fuzzy technique in which three different algorithms have been used to tune the network parameters. The usage of gas to tune an RBF network based fuzzy model without membership functions is discussed.[14,15]

MATERIALS AND METHODS

Based on the fact that an accurate control of thermal dosage is essential for effective hyperthermia treatment, the proposed research work aims to design an efficient controller that is hybrid in nature and provides accurate results. Computer Simulation Studies of the same has been carried out by deriving the mathematical model of the human tissue.

The modeling of the tissue poses the following control problems: It is required to attain the optimum value of thermal dose, Df, applied on the tumor using non-invasive ultrasound power deposition technique. In order to reduce side effects, the maximum allowable temperature limits are imposed on the temperature to which normal tissues surrounding the tumor are exposed. It is further essential to reduce the time for treatment t_f within the temperature constraints imposed. The methodology to derive the thermal model of the human tissue is shown in Fig.2.

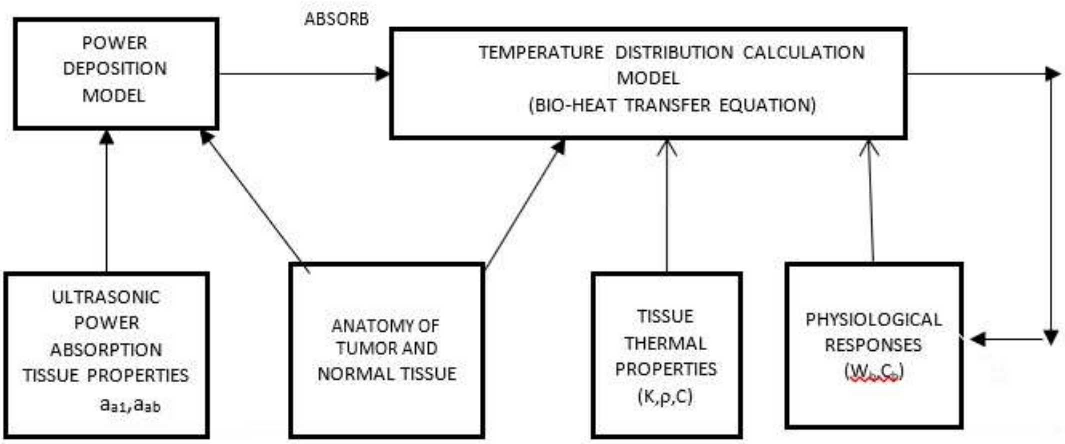

Fig.2. Procedure to derive Mathematical Model of a Tissue

Thermal Model of Tissue

The transport of heat energy in a human tissue is represented mathematically as given in Eq (1) which is a semi empirical model,

$$\rho C \frac{\partial T}{\partial t} = \nabla(k\nabla T) - W_b \; C_b \; (T - T_a) + Q \quad (1)$$

C, C_b - Specific Heat Capacity of tissue and blood (J/Kg^{0}C)
W_b - Perfusion of Blood [Kg/(m3 s]
Ta - Arterial Temperature (assumed to be 37^{0}C)
Q - Deposition of Power in the tissue in W/m^3)

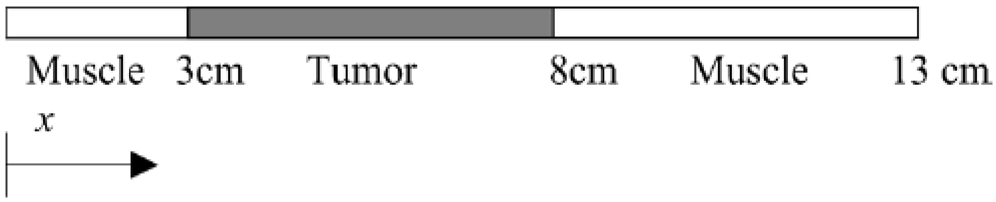

Fig 3. One-dimensional tissue model.

The controller performance for the heat treatment is verified using a 1D model of the tissue shown in Fig. 3 and the model is reduced to Eq. 2

$$\rho C \frac{\partial T}{\partial t} = k \frac{\partial^2 T}{\partial x^2} - W_b \; C_b \; (T - T_a) + Q \quad (2)$$

Constant Conductivity has been assumed and $x \in [0,13]$ is the penetration depth in the tissue. At both skin surfaces, it is assumed that T=T_b. The acoustic and thermal properties of each region is given in Table 1.

Table 1. Properties of Human Tissue

Component	Tissue Property			
	Thermal Conductivity K (W/(M°C)	Density ρ (Kg/m3)	Heat Capacity C=Cb (J/(Kg°C)	Surface Tension α (N/M)
Muscle	0.64	1000	3500	18.5
Tumor	0.57	1000	4000	20.5

Thermal Dose

The thermal dose, D, can be used to characterize the effect of temperature and the time of treatment on the thermal therapy as given in Eq.

$$D = \int_{0}^{tf} R^{(43-T(t))}\, dt, \quad where \;\; R = \begin{cases} 0.25 & for \;\; T(t) < 43^{\circ}C \\ 0.50 & for \;\; T(t) \geq 43^{\circ}C \end{cases} \tag{3}$$

where t_f - Final value of time when the thermal dose is integrated.
The thermal dose is represented in units of equivalent minutes at 43°C.

State Space Formulation
After finite dimensional approximation, the bio-heat transfer model (5,6) is expressed in the state-space form as given below.

$$\dot{T} = AT + B\,u$$
$$T_{90} = s(t)$$

Where A- System Matrix including perfusion and conduction
B – Input matrix determined by Eq.(4)

Feedforward Controller
The control problem can be formulated as finding a controller K_D that maps the desired final thermal dose D_f as shown in Fig.4.

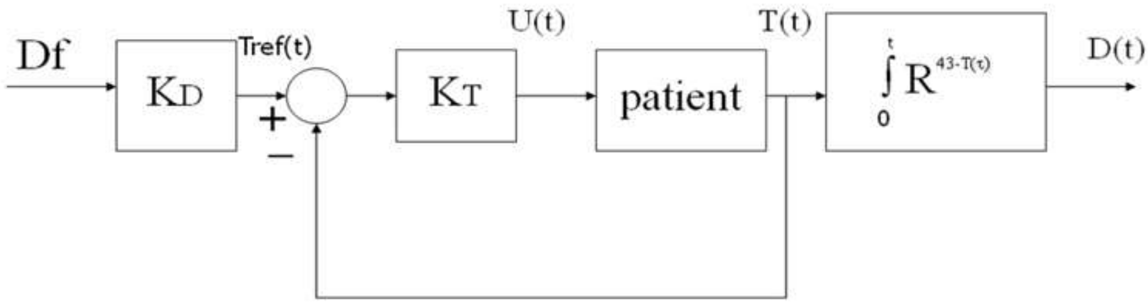

Fig.4. Feed forward controller of thermal dose.

KT - Temperature controller
Df - Desired Final thermal dose
KD - Feed forward Control

KD:Df →T(t,u(t))=Tref(t),t ϵ[0,tf] (7)

Intelligent Thermal Dose Controller
In order to develop a database and decision support system for the patient, it is necessary to design an intelligent, adaptive controller

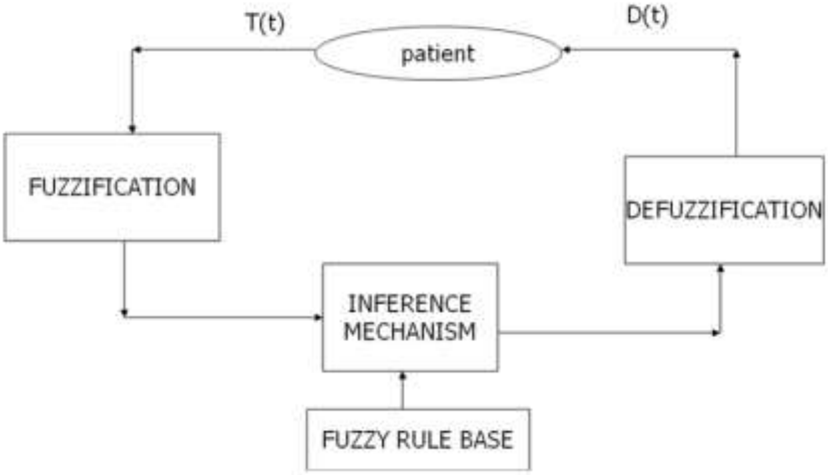

Fig.5. Block Diagram of Fuzzy Logic Based Thermal Dose Controller

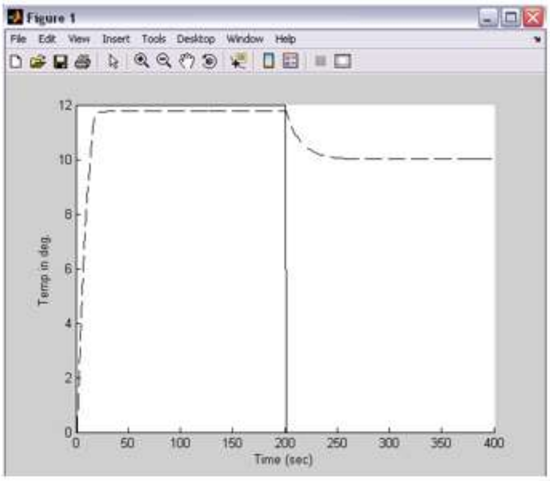

Fig.6a. Response of Temperature Control

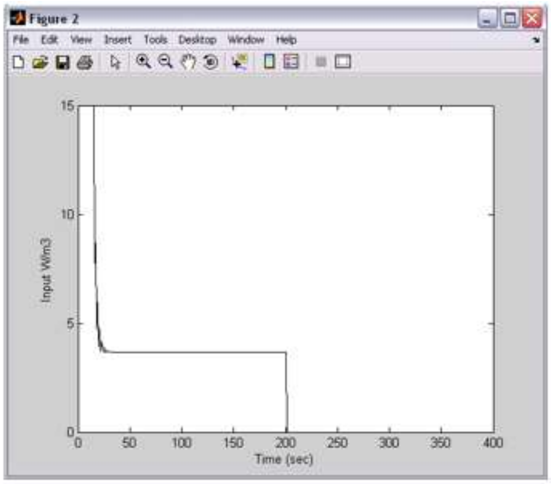

Fig. 6b. Controlled Ultrasound Power

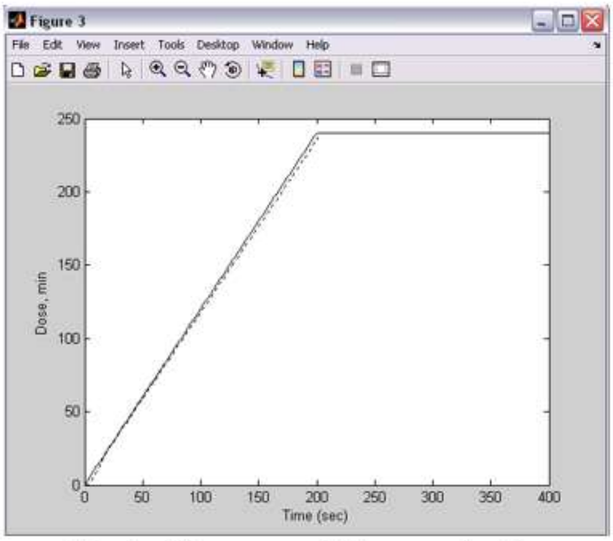

Fig. 6c. Response of Dose controller

Fig.6. Performance of Thermal Dose Controller using FLC with Linear Parametrization

The thermal dose controller response for Fuzzy Controller with exponential parametrization is shown in Fig. 7a to Fig. 7c.

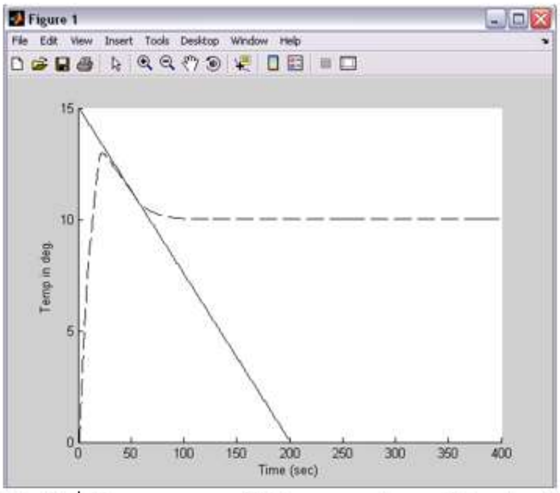

Fig.7a. Response of Temperature Controller

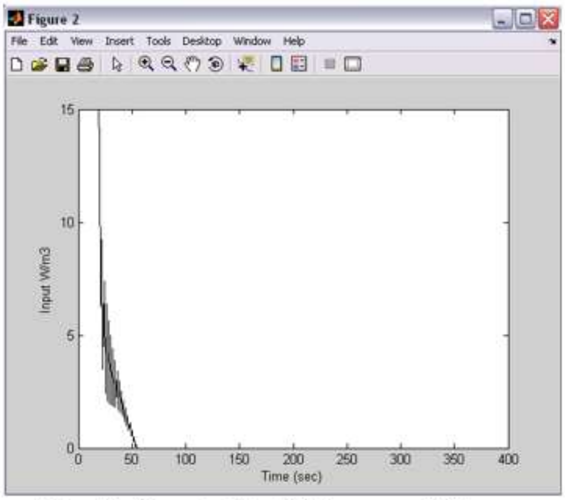

Fig. 7b.Controlled Ultrasound Power

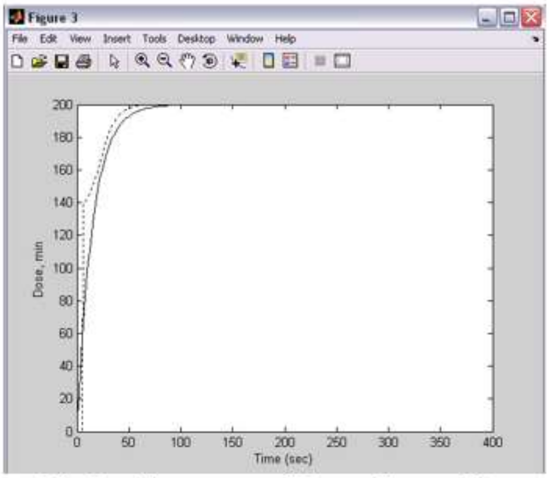

Fig.7c. Response of Dose Controller

Fig.7 Performance of Thermal Dose Controller using FLC with Exponential Parametrization

Table 2: Performance of Thermal Dose Controller with Fuzzy Logic Controller

Set Point	**Rise Time (Minutes)**		**Settling Time (Minutes)**		**Mean Square Error (Model Validation)**	
12^{0} C	**FLC (Linear)**	**FLC (Exponential)**	**FLC (Linear)**	**FLC (Exponential)**	**FLC (Linear)**	**FLC (Exponential)**
	11.756	11.956	10	10	7.2914	8.0094

FALCON Based Thermal Dose Controller

The simulation of FALCON based thermal dose controller was done for both linear and exponential parametrization and the results obtained are shown from Fig. 8a to Fig.8c.

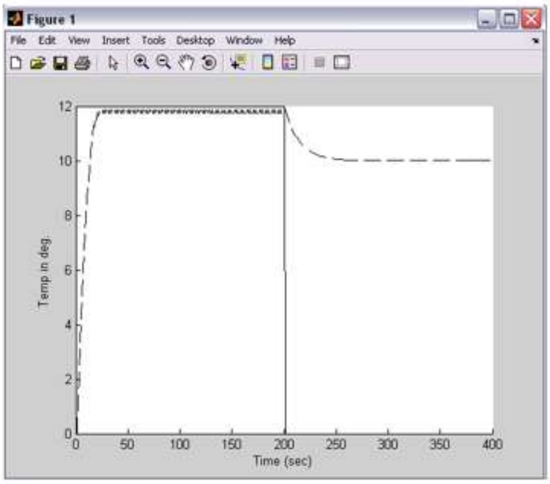

Fig.8a. Response of Temperature Controller

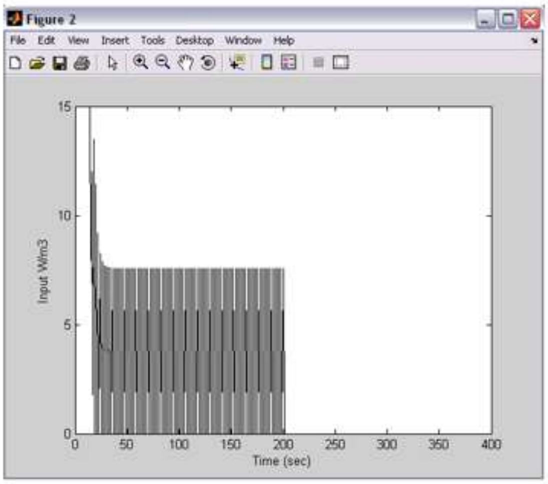

Fig. 8b. Controlled Ultrasound Power

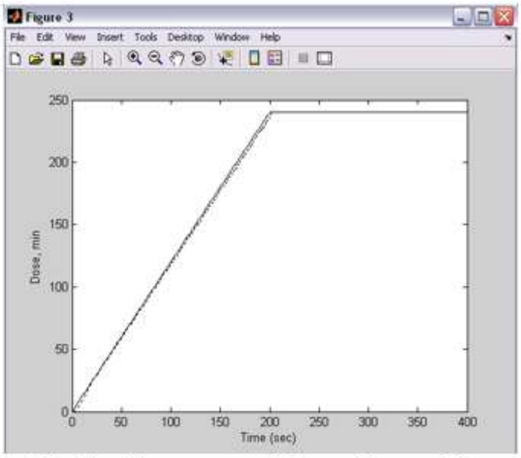

Fig.8c. Response of Dose Controller

Fig.8. Performance of Thermal Dose Controller using FALCON with Linear Parametrization

Thermal Dose Controller performance based on FALCON with exponential parametrization is shown in Fig.9a. to Fig. 9c

The synergistic integration of fuzzy logic and neural networks helps improve controller performance. Fuzzy logic is fault tolerant and is effectively used for imprecisely defined non-linear systems. The most important issue in designing an FLC is the derivation of optimum fuzzy rules and parameter adaptation. The Neural Networks on the other hand exhibit powerful learning, adaptation and optimization capabilities. The computational capabilities of FLC and neural networks can be combined to form an Adaptive Fuzzy Controller, viz., Fuzzy Adaptive Learning Control Network (FALCON) that modifies the rule characteristics, topology and structure of fuzzy control systems. The intelligent control strategy is depicted in Fig. 5. The thermal dosage control in the proposed work is implemented using the basic feedforward mechanism that uses a simple fuzzy logic controller as well as a neuro fuzzy controller and the performance is compared using the performance metrics like rise time, settling time of the system response.

RESULTS AND DISCUSSION

The thermal model of the tissue was simulated using simulation software tools to implement a fuzzy logic controller for two different parametrization, viz., linear and exponential. The results of simulation is shown from Fig. 6a to Fig.6c. Temperature deviation from thermal equilibrium of Ta = 370^0 C is assumed for all simulations. The most simple case of a "single-point" target has been considered in this research work.

The thermal dose controller response, the controlled ultrasound power and the thermal dose for a fuzzy controller with linear parametrization is shown in Fig. 6a to Fig. 6c. The solid lines in the figures indicate the set point trajectory for temperature and thermal dose whereas the dashed lines indicate the response of proposed controller.

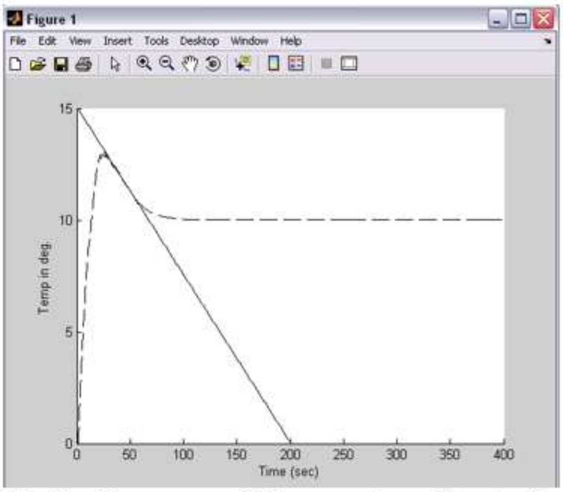

Fig.9a. Response of Temperature Controller

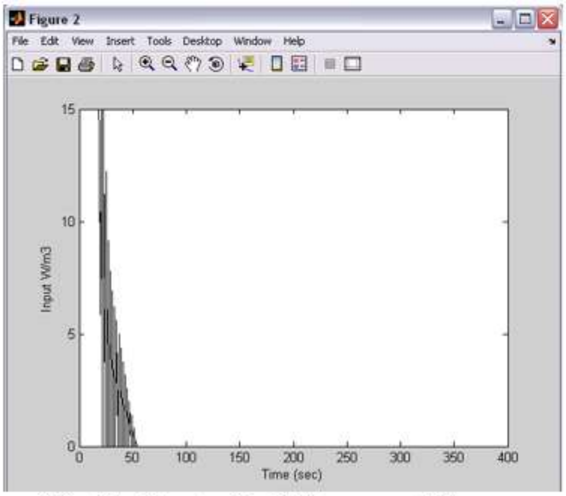

Fig.9b. Controlled Ultrasound Power

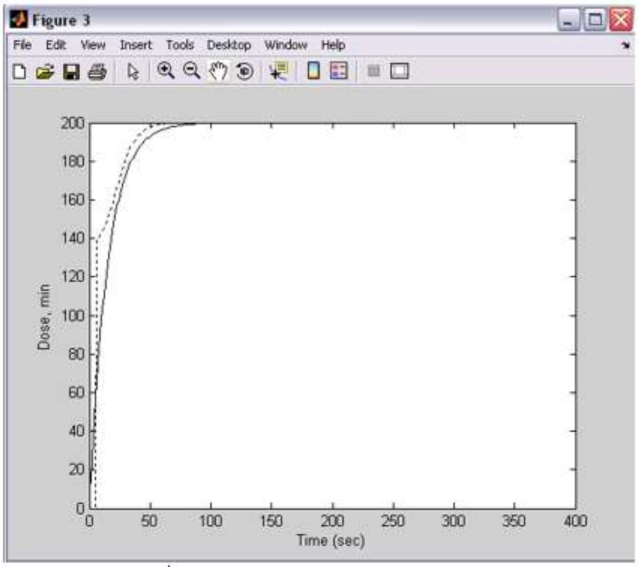

Fig. 9c. Response of Dose Controller

Fig.9. Performance of Thermal Dose Controller using FALCON with Exponential Parametrization

Table 3: Performance of Thermal Dose Controller with FALCON

Set Point(^{0}C)	Rise Time (Minutes)		Settling Time (Minutes)		Mean Square Error (Model Validation)	
	FALCON (Linear)	**FALCON (Exponential)**	**FALCON (Linear)**	**FALCON (Exponential)**	**FALCON (Linear)**	**FALCON (Exponential)**
12	11.877	11.928	10	10	7.2851	8.0093

Comparison of performance of FLC and FALCON Based controllers for thermal dosage.

The performance of thermal dose controller using FLC as well as FALCON has been analyzed and the controller parameters have been evaluated for both the cases. The results indicate that there is significant improvement in controller performance characteristics between the two control strategies adopted.

Table 4: Comparison of performance of FLC and FALCON Based Thermal Dose Controller

Set Point (^{0}C)	Rise Time (Minutes)				Settling Time (Minutes)				Mean Square Error (Model Validation)			
	Linear		Exponential		Linear		Exponential		Linear		Exponential	
	FLC	FALCON	FLC	FALCON	FLC	FALCON	FLC	FALCON	FLC	FALCON	FLC	FALCON
12	11.756	11.877	11.956	11.928	10	10	10	10	7.2914	7.2851	8.0094	8.0093

CONCLUSION

The significance of designing an optimum thermal dosage controller for appropriately administering the thermal dose to the affected carcinogenic tissues without damaging the neighboring normal tissues is discussed. In order to evaluate the controller performance, the thermal model of the tissue has been derived based on conventional concepts and simulated in software tool. The performance of intelligent feed forward control mechanism like FLC, FALCON have been simulated and the results have been analyzed. From the results obtained, it can be inferred that the proposed hybrid approach is effective in delivering the required thermal dose in a minimum time confining to the restrictions on the maximum allowable temperature in order to prevent damages to healthy tissue. The controller that is developed is applicable to wide range of intensities and is found to be suitable for heat treatment therapy in association with radiation therapies.

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REFERENCES

1. Ellen L. Jones, James R. Oleson, Leonard R. Prosnitz, Thaddeus V. Samulski, Zeljko Vujaskovic, Daohai Yu, Linda L. Sanders, and Mark W. Dewhirst, Randomized Trial of Hyperthermia and Radiation for Superficial Tumors, Journal of Clinical Oncology, 2005, 23 (13), 3079-3085, 2005. DOI: : 10.1200/JCO.2005.05.520
2. J. Van der Zee and M. C. C. M. Hulshof, "Lessons learned from hyperthermia," Internationla Journal of Radiation and Oncology, Biology,Physics, 2003, 57(2) 596–597. DOI: 10.1016/S0360-3016(03)00363-8
3. Kullervo Hynynen, Oliver Pomeroy, Darrell N. Smith, Peter E. Huber, Nathan J. Mc Dannold, Joachim Kettenbach, Janet Baum, Samuel Singer, Ferenc A. Jolesz, MR imagingguided focused ultrasound surgery of fibroadenomas in the breast: A feasibility study, Radiology,2001,219(1),176–185.DOI:10.1148/radiology.219.r01ap02176
4. E. Gelvich and V. Mazokhin, " Contact flexible microstrip applicators (CFMA) in a range from microwaves up to short waves," IEEE Transactions on Biomedical Engineering, 2002, 49 (9), 1015–1023. DOI: 10.1109/TBME.2002.802053
5. P. Stauffer, S. Jacobsen, D. Neuman, and F. Rossetto, "Progress toward radiometry controlled conformal microwave array hyperthermia applicator," Proceedings of the 22nd Annual International Conference of the IEEE Engineering in Medicine and Biology Society (Cat. No.00CH37143), 2000, 4, 1613 – 1616. DOI: 10.1109/IEMBS.2000
6. L. Dubois, J.-P. Sozanski, V. Tessier, J. Camart, J.-J. Fabre, J. Pribetich, and M. Chive, "Temperature control and thermal dosimetry by microwave radiometry in hyperthermia," IEEE Transactions on Microwave Theory andTechniques, 1996, 44 (10), 1755–1761. DOI: 10.1109/22.539932.
7. P. VanBaren and E. Ebbini,Multipoint temperature control during hyperthermia treatments: theory and simulation, IEEE Transactions on Biomedical Engineering,
8. 1995, 42 (8), 818–827. DOI: 10.1109/10.398643.
9. L. Zhou and P. Fessenden, "Automation of temperature control for large-array microwave surface applicators," Int. J. Hypertherm., vol. 9, no. 3, pp. 479–490, 1993.
10. D. Arora, M. Skliar, and R. Roemer, "Model-predictive control of hyperthermia treatments," IEEE Trans. Biomed. Eng., vol. 49, no. 7, pp. 629–639, Jul. 2002.
11. H. Pennes, "Analysis of tissue and arterial blood temperatures in resting human
12. forearm," J. Appl. Physiol., vol. 1, pp. 93–122, 1948.
13. H. R. Berenji, "Learning and Tuning Fuzzy Logic Controllers Through Reinforcements", IEEE Transactions on Neural Networks, Vol. 3, 1992, pp. 724-740.
14. A.Varsek, T. Urbancic, and B. Filipic, "Genetic Algorithms in Controller Design and Tuning", IEEE Transactions on Systems, Man & Cybernetics, Vol. 23, 1993.

15. W. A. Farag, V. H. Quintana, and G. Lambert-Torres, "A Genetic-Based Neuro-Fuzzy Approach for Modelling and Control of Dynamical Systems", IEEE Transactions on Neural Networks, Vol. 9, No. 5, 1998, pp. 756-767.
16. T. L. Seng, M. B. Khalid, and R. Yusof, "Tuning of a Neuro-Fuzzy Controller by GeneticAlgorithm", IEEE Transactions on Systems, Man & Cybernetics, Vol. 29, 1999, pp. 226-236.
17. T. Takagi and M. Sugeno, "Fuzzy Identification of Systems and Its Applications to Modelling and Control", IEEE Transactions on Systems, Man & Cybernetics, Vol. 15, 1985.
18. Dhiraj Arora ,Mikhail Skliar,Robert B. Roemer,Minimum-Time Thermal Dose Control of Thermal Therapies, IEEE Trans. Biomed.Eng., vol. 52, no.2,february 2005.
19. Jessi E. Johnson , Paolo F, Daniel Neuman , Automatic Temperature Controller for Multielement Array Hyperthermia Systems, IEEE Trans. Biomed. Eng., vol. 53, no. 6, June 2006.