



Artificial Neural Network Based Primed Cathode A6 Magnetron for Improving the Efficiency of Microwave Heating Systems.

Eze Emmanuel Ejike, J. Eke, Emetu Chukwuma Kalu.

Enugu State Nigeria

Department of Electrical and Electronic Engineering, Enugu State University of Science and Technology, Enugu State Nigeria

Spytechworld Engineering Ltd, Enugu State Nigeria

Ejikeemmanuel78@yahoo.com, drjimmyeke@yahoo.com, chukskay@gmail.com

ABSTRACT

Microwave heating systems are used in homes, manufacturing lines and industries for heating food and industrial microwavable objects. These microwave heating systems though being environmentally friendly and a routine appliance consumes a lot of power which constitutes burden and expenditures on individuals and industries who utilize them for heating their materials. Available literatures did not consider the use of magnetron priming to improve the efficiency of microwave heating systems. In this paper, a Function Fitting Neural Network (FFNN) based cathode priming technique was proposed for improving the efficiency of microwave heating systems. The Panasonic microwave oven (model NN-SN966S) was used as the test bed for carrying out the research. Six foods (beefs, Pork and lamb, chicken, shrimps, sardines and tomatoes) were selected for the analysis. The development of an efficiency model of the Panasonic microwave oven as well as the A6 relativistic magnetron model was achieved using the Matlab and Simulink environment. A Function Fitting Neural Network (FFNN) was developed/trained and integrated with the microwave oven model for the purpose of priming its cathode. From the simulation results it was observed that the integration of the microwave oven model with the FFNN based A6 relativistic magnetron increased the oven's cooking temperature by 5.4639%, reduced the cooking time by 6.3028% and improved the overall efficiency of the microwave oven by 11.82%.

INDEX TERMS - Microwave Oven, Panasonic Microwave Oven, FFNN, Cathode, Food, Magnetron

I. 1. Introduction

Microwave heating systems are systems where microwaves generated by magnetrons are projected toward the target medium or reactants, which absorb the electromagnetic energy volumetrically to achieve self-heating quickly and uniformly [6] [14] [11]. According to [3], when compared to traditional heating methods, microwave heating technology has significant advantages such as greater selectivity and chemical reaction rate, rapid volumetric heating, higher product yield, and shorter reaction time. Additionally, a variety of liquid solvents and their appropriate mixtures will offer a great deal of flexibility for the quick microwave synthesis of different types of nanostructured materials, as well as control over their self-assembly, morphology, size, structure, and chemical composition [2] [10]. This will significantly broaden the applications of microwave heating technology in materials science. As a result, the microwave heating system provides a revolutionary heat source for the quick chemical reactions and materials synthesis that can be done in a matter of minutes as opposed to the hours or even days that are often needed by conventional heating technique [3] [13].

In the manufacturing and food service industries, microwave heating devices are frequently employed for applications requiring rapid heating. However, there are a number of issues that industrial microwave system or microwave oven customers face, namely uneven heating [5] [7]. According to [4], food geometry, food physical characteristics, and microwave cavity design are among the variables that affect uneven microwave heating. These variables influence how the microwave field is spread throughout foods and ovens. Several interacting variables relating to the microwave oven, packaging, and the food itself will impact how the food is heated during microwave cooking. Multi-component foods frequently necessitate custom product creation in order to avoid uneven heating, which could otherwise produce difficulties with both microbiological and sensory quality.

II. 2. Literature Review

Many researchers have conducted a study on how to optimize the parameters of the Microwave magnetron for improving the efficiency of Microwave heating systems. This section gives a review of the previous works that have been carried out in this research area.

[8] in their work "A Multiple Local Model Learning for Nonlinear and Time-Varying Microwave Heating Process" presented a numerous local model learning strategy for a non-stationary and nonlinear microwave heating process. Model adaptation is carried out by the suggested local learning framework

on two different levels: (1) online modification of model prediction, which chooses a subset of potential local linear models as well as radially integrates them to develop the model prediction; and (2) modifications of the local generalized linear set, which recursively divides the process's data into various sub processes, each integrated with a local linear model. To show the suggested numerous local model learning approaches improved performance in terms of computing effectiveness and online modeling accuracy, they employed a case study comprising a real-world industrial MHP. The outcome of their study depicted that their suggested method, for non-stationary and non-linear modeling, not only achieves greater online prediction accuracy than the SO-ELM, but also imposes much lower online compute complexity per sample. Therefore, their method can be used for general non-stationary and nonlinear systems.

[12] in their work “A Temperature-Control System for Continuous-Flow Microwave Heating Using a Magnetron as Microwave Source” developed a real-time temperature control system for a substance that flows continuously to be heated by a microwave. In this system, a magnetron is employed as the microwave source and its output power is continually adjustable by circuit design. The power and temperature data are processed by a programmable logic controller (PLC), which also directs the entire control choice. Their findings indicate that the suggested system may successfully reach the specified temperature with a respectable level of accuracy and stability.

[9] in their work “Application of Neural Networks: Enhancing Efficiency of Microwave Design”, presented the technique for creating neural models of microwave structures using a computer. To overcome the key training issues of traditional neural nets, artificial neural networks are trained utilizing a mix of the quasi-Newton technique and particle swarm optimization throughout the construction phase. The researchers utilized neural networks to simulate the behavior of a planar microwave filter (Zeland IE3D, moment method). To assess the effectiveness of neural modeling, global optimizations are carried out using both neural and numerical models. The feed-forward neural model trained using the Levenberg-Marquardt algorithm and the particle swarm technique was shown to be the most accurate and quickest way to simulate a low pass planar filter. However, the recurrent model of their ANN was not able to be trained with the sufficient accuracy.

[6] in their work “Neural Networks for Microwave Modeling: Model Development Issues and Nonlinear Modeling Techniques”, reviewed two important aspects of Neural network based microwave modeling, namely nonlinear modeling and model development issues. They also presented a systematic description of key issues in the neural modeling approach, such as distribution and range of samples in model input parameter space, data scaling, data generation and so on. They also discussed recent techniques, such as adaptive sampling and adaptive controller that could lead to automatic neural model development. They discussed nonlinear methods such as dynamic recurrent neural network (RNN) circuit modeling and tiny big signal neural modeling of transistors. They came to the conclusion that further development and research is needed to fully realize the potential of neural networks, and that automated neural modeling of CAD tools is critical. The limitation of their research is that the number of neurons in their model is only 3. This does not guarantee efficient operation of the ANN.



Figure 1: Panasonic Microwave Oven (Front View)

[1], in their work “Approach for Efficiency Enhancement of Microwave Ovens”, showed the improvement of the output performance of a home microwave oven. Using the test method described in the IEC 60705, they estimated the oven's efficiency and power output. They modeled the magnetron using CST studio suite software's 3-D particle in cell modelling to evaluate its performance. To simulate the -quadrupole of a non-linear transformer, they utilized the Matlab and Simulink environments. According to their findings, there is only around a 5.04% difference between the experimental and simulated values. In addition, the oven's performance has been improved by around 4.52 percent.

III. 3. Methodology

Figure 1 shows the front view of the Panasonic microwave oven (NN-SN966S Model). The Panasonic microwave oven has a 16.5 inch turn table. Figure 2 shows the specifications of the Panasonic microwave oven model NN-SN966S obtained from the manufacturer's website

| Specifications | |
|-----------------|-------|
| Capacity | 62L |
| Maximum Output | 1250W |
| Smart Sensors | Yes |
| Preset Settings | 14 |

Figure 2: Specifications of the Panasonic Microwave Oven (Model NN-SN966S).

The Cooking times and temperature data of the Panasonic Microwave Oven (Model NN-SN966S) for different food products were also obtained from the Panasonic microwave oven manufacturers. From the cooking times and cooking temperature data, the different foods for carrying out the research was extracted alongside their cooking data. The formula for determining the overall efficiency of the microwave oven was

derived and an experiment was carried out with the help of the cooking data of the selected foods in order to characterize the effects of varying or fluctuating power supply on the overall efficiency of the microwave oven. The experiment was carried out by applying different input power to the microwave oven and then recording the response of the selected foods under the power fluctuation issue. The responses recorded are the cooking time, cooking temperature and overall cooking efficiency of the microwave oven.

In a microwave oven magnetron, the connection between electron cloud, magnetic field strength, phase velocity and drift velocity of the slow wave structure of the anode block are all essential for RF generation. The following formula in Equation 1 gives the drift velocity V_d of the electron clouds inside the magnetron.

$$V_d = \frac{E \times B}{|B|^2} \quad (1)$$

E is the radial electric field vector, B is the axial magnetic field vector, and $|B|$ is the magnetic field magnitude. Equation 2 gives the phase velocity V of the electromagnetic field produced by the anode block's slow wave structure.

$$V_\theta = \frac{E_r}{B_z} \quad (2)$$

Where B_z denotes the azimuthal magnetic field and E_r denotes the radial electric field. The potential energy of the electrons released from the cathode must be transmitted to the RF field in order for the potential energy of the electrons emitted from the cathode to be transferred to the RF field.

$$V_\theta = V_d \quad (3)$$

That is, the slow wave structure's phase velocity and the electron cloud's drift velocity are in phase with one another. Resonance creates the ideal environment for energy transfer. The Buneman-Hartree (B-H) synchronous condition describes the resonant state.

In the production of microwaves, the phase velocity of the slow wave structure, electric field intensity, and the magnetic field intensity all play critical synchronous roles. In order for oscillations to occur, two conditions must be met. The Hull cut-off condition, as described in Equation 4, is the first of these.

$$B_c = \frac{mc}{ed_e} (\gamma^2 - 1)^{\frac{1}{2}} = \frac{mc}{ed_e} \left[\left(\frac{2eV}{mc^2} \right)^2 + \left(\frac{eV}{mc^2} \right)^2 \right]^{\frac{1}{2}} \quad (4)$$

e is the electron charge, B_c is the magnetic field's value, c is the speed of light, V is the voltage across the anode-cathode (A-K) gap, d_e is the effective gap in the cylindrical geometry provided by Equation 4 and m is the electron's mass.

$$d_e = \frac{r_a^2 - r_c^2}{2r_a} \quad (5)$$

The radius of the cathode is r_c and the radius of the anode is r_a . Electrons will travel back to the cathode if the magnitude of the axial magnetic field is too large. Electrons will go straight to the anode if this field is too weak or missing. The magnetic field and electric field strengths must be optimized such that the spinning electron cloud in the cavity is contained to the cavity and the cloud hardly contacts the anode. The B-H condition (Equation 6) is the second condition required for oscillations.

$$B_{BH} = \frac{mc^2 n}{|e| \omega_n r_a d_e} \left(\frac{|e|V}{mc^2} + 1 - \sqrt{1 - \left(\frac{r_a \omega_n}{cn} \right)^2} \right) \quad (6)$$

The mode number is n and the frequency mode of interest is $\omega_n = 2\pi f$. With increasing magnetic field, the drift velocity V_d given in Equation 1 decreases. This implies that the electrons are too sluggish to be resonant above a certain axial magnetic field. The B-H and Hull cut-off conditions work together to define a specific operating area involving axial magnetic and radial electric field intensities. To summarize, the magnetic field intensity must be strong enough to prevent electrons from reaching the anode block, but not so strong that the electrons are slowed to the point where the drift velocity is too slow for resonance. The magnetic field range for oscillation, the Hull cut-off condition, and the BH condition, are all depicted graphically in practice.

Making V the subject of the formula in Equation 6, then

$$\begin{aligned} \frac{B_{BH}|e|\omega_n r_a d_e}{mc^2 n} &= \frac{|e|V}{mc^2} + 1 - \sqrt{1 - \left(\frac{r_a \omega_n}{cn} \right)^2} \\ \frac{B_{BH}|e|\omega_n r_a d_e}{mc^2 n} - 1 + \sqrt{1 - \left(\frac{r_a \omega_n}{cn} \right)^2} &= \frac{|e|V}{mc^2} \\ V &= \frac{mc^2}{|e|} \left(\frac{B_{BH}|e|\omega_n r_a d_e}{mc^2 n} - 1 + \sqrt{1 - \left(\frac{r_a \omega_n}{cn} \right)^2} \right) \end{aligned} \quad (7)$$

Equation 7 gives the formula for computing the output voltage of the microwave oven magnetron. The output power of the microwave oven can be determined from the output voltage using the relation:

$$P = IV \quad (8)$$

Where,

P = the power rating/output power of the magnetron

V = voltage across the anode-cathode gap/output voltage

I = Output current of the magnetron.

Putting Equation 7 into Equation 8 yields,

$$P = I \times \left(V = \frac{mc^2}{|e|} \left(\frac{B_{BH}|e|\omega_n r_a d_e}{mc^2 n} - 1 + \sqrt{1 - \left(\frac{r_a \omega_n}{cn} \right)^2} \right) \right) \quad (9)$$

The electrical energy used by the microwave oven is calculated using the formula:

$$P = \frac{E}{t} \quad (10)$$

Where,

P = the power rating/output power of the magnetron

E = the electrical energy used by the microwave oven (Joules)

t = the time the microwave oven was turned ON

The amount of energy converted into heat is calculated using the formula:

$$Q = mC_{food} (T_{final} - T_{initial}) \quad (11)$$

Where,

Q = the heat lost to the surroundings

M = mass of the food being heated

T_{final} = the final temperature of the food being heated

$T_{initial}$ = the initial temperature of the food being heated

C_{food} = specific heat of the food being heated.

Hence the percentage efficiency of the microwave oven is worked out using the relationship:

$$\text{Percentage efficiency} = \frac{E-Q}{E} \times 100 \quad (12)$$

Substituting Equations 10 and 11 into 12 yields:

$$\text{Percentage efficiency} = \frac{pt - mC_{food}(T_{final} - T_{initial})}{pt} \times 100$$

$$1 - \frac{mC_{food}(T_{final}-T_{initial})}{pt} \times 100 \quad (13)$$

Substituting the value of p in Equation 9 into Equation 13 yields,

$$\text{Percentage efficiency} = 1 - \frac{mC_{food}(T_{final}-T_{initial})}{t \times \left(V = \frac{mc^2}{|e|} \left(\frac{B\mu H |e| \omega_n r_a d_e}{mc^2 n} - 1 + \sqrt{1 - \left(\frac{r_a \omega_n}{cn} \right)^2} \right) \right)} \times 100 \quad (14)$$

Since the power rating of the Panasonic microwave oven (P_R) is known (1250 watts), and the voltage rating (V_R) is 220V, then other parameters can be computed as follows:

$$\text{Current rating } (I_R) = \frac{P}{V_R} = \frac{1250}{220} = 5.68 \text{ Amps}$$

Hence,

$$\frac{V_R}{V} = \frac{I}{I_R}$$

$$\text{and } I = \frac{V_R}{V} \times I_R \quad (15)$$

$$I = \frac{220}{110} \times 5.68 = 11.36 \text{ Amps}$$

Other parameter values for Equation 14 includes:

$$r_a = 2.11 \text{ cm} = 0.0211 \text{ m}$$

$$r_c = 1.58 \text{ cm} = 0.0158 \text{ m}$$

$$\omega_n = 2\pi f = 2 \times \pi \times 2.46 \times 10^6 = 15456635.86$$

$$d_e = \frac{r_a^2 - r_c^2}{2r_a} = 4.634 \times 10^{-3}$$

$$n = 3$$

$$\text{mass of electron } (m) = 9.11 \times 10^{-31} \text{ kg}$$

$$\text{Charge of electron } (e) = 1.6 \times 10^{-19} \text{ Coloumbs}$$

$$\text{Speed of Light } (c) = 3 \times \frac{10^8 \text{ m}}{\text{s}}$$

$$\text{Magnetic flux density} = 0.22 \text{ Tesla}$$

Table 1 shows the cooking data of the selected foods. This Table is extracted from the cooking times and cooking temperature table of the Panasonic microwave oven in order to help in computing the efficiency of the Panasonic microwave oven.

Table 1: Cooking data of some selected Foods

| Food | Mass of food (Kg) | Specific heat of Food (J/Kg/°C) | Initial/Ambient Temperature (°C) | Final Temperature (°C) | Measured Cooking Time (Seconds) |
|---------------|-------------------|---------------------------------|----------------------------------|------------------------|---------------------------------|
| Beef | 1.2056 | 3440 | 24 | 201 | 1147.5 |
| Pork and Lamb | 1.4283 | 2800 | 24 | 201 | 1072.5 |

| | | | | | |
|----------|--------|------|----|-----|------|
| Chicken | 1.7316 | 3350 | 24 | 192 | 1464 |
| Shrimps | 0.3135 | 3400 | 24 | 204 | 300 |
| Sardines | 0.9475 | 3000 | 24 | 193 | 750 |
| Tomatoes | 0.2336 | 3860 | 24 | 204 | 240 |

From all the information given, the efficiency of the Panasonic microwave oven model N-SN966S is computed as follows:

Beef

$$V = \left(\frac{9.11 \times 10^{-31} \times (3 \times 10^8)^2}{1.6 \times 10^{-19}} \right)$$

$$\times \left(\frac{0.22 \times 15456635.86 \times 0.0211 \times 4.634 \times 10^{-3}}{9.11 \times 10^{-31} \times ((3 \times 10^8)^2) \times 3} - 1 + \sqrt{1 - \left(\frac{0.0211 \times 15456635.86}{3 \times 10^8 \times 3} \right)^2} \right)$$

$$= 512437.5(0.00021630686 - 1 + 0.9999997373)$$

$$110.709 \text{ Volts}$$

Then,

$$\eta_{oven} = 1 - \frac{1.2056 \times 3440 \times (201 - 24)}{1147.5 \times 1250} \times 100$$

= 48.82%

Pork and Lamb

$$\eta_{oven} = 1 - \frac{1.4283 \times 2800 \times (201 - 24)}{1072.5 \times 1250} \times 100$$

= 47.20%

Chicken

$$\eta_{oven} = 1 - \frac{1.7316 \times 3350 \times (192 - 24)}{1464 \times 1250} \times 100$$

= 46.75%

Shrimps

$$\eta_{oven} = 1 - \frac{0.3135 \times 3400 \times (204 - 24)}{300 \times 1250} \times 100$$

= 48.84%

Sardines

$$\eta_{oven} = 1 - \frac{0.9475 \times 3000 \times (193 - 24)}{750 \times 1250} \times 100$$

= 48.76%

Tomatoes

$$\eta_{oven} = 1 - \frac{0.2336 \times 3860 \times (204 - 24)}{240 \times 1250} \times 100$$

= 45.90%

Under random/fluctuating power supply, the

microwave oven rather than operate normally, makes some humming noise and thereby reducing its productivity. Some random/fluctuating power used in the experiment includes: 1250, 1200, 1150, 1100, 1050, 1000, 950, 900, 850, 800, 750, 700, 650 Watts etc.

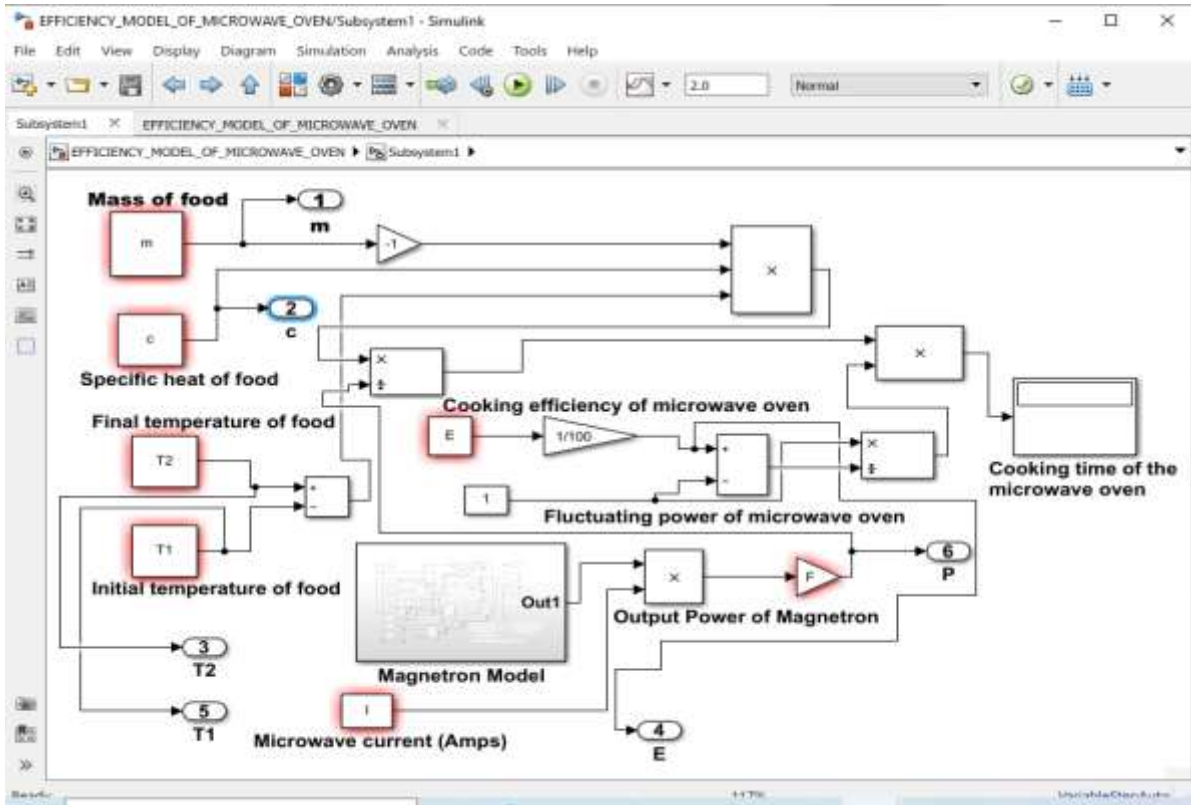


Figure 3: Model of cooking time of the microwave oven

1) 3.1. Effects of Power fluctuation on Cooking Time

From Equation 3.13

$$\eta_{Oven} = 1 - \frac{mC_{food}(T_{final}-T_{initial})}{pt} \times 100$$

$$\left(\frac{\eta_{Oven}}{100} - 1\right) = -\frac{mC_{food}(T_{final} - T_{initial})}{pt}$$

$$t\left(\frac{\eta_{Oven}}{100} - 1\right) = -\frac{mC_{food}(T_{final} - T_{initial})}{p}$$

$$t = -\frac{mC_{food}(T_{final}-T_{initial})}{p} \times \frac{1}{\left(\frac{\eta_{Oven}}{100}-1\right)} \quad (16)$$

2) 3.2 Effects of Power fluctuation on cooking temperature

$$\eta_{Oven} = 1 - \frac{mC_{food}(T_{final}-T_{initial})}{pt} \times 100$$

$$\left(\frac{\eta_{Oven}}{100} - 1\right) = -\frac{mC_{food}(T_{final} - T_{initial})}{pt}$$

$$\frac{pt}{mC_{food}}\left(\frac{\eta_{Oven}}{100} - 1\right) = -(T_{final} - T_{initial})$$

$$\frac{pt}{mC_{food}}\left(\frac{\eta_{Oven}}{100} - 1\right) = -T_{final} + T_{initial}$$

$$T_{final} = T_{initial} - \frac{pt}{mC_{food}}\left(\frac{\eta_{Oven}}{100} - 1\right) \quad (17)$$

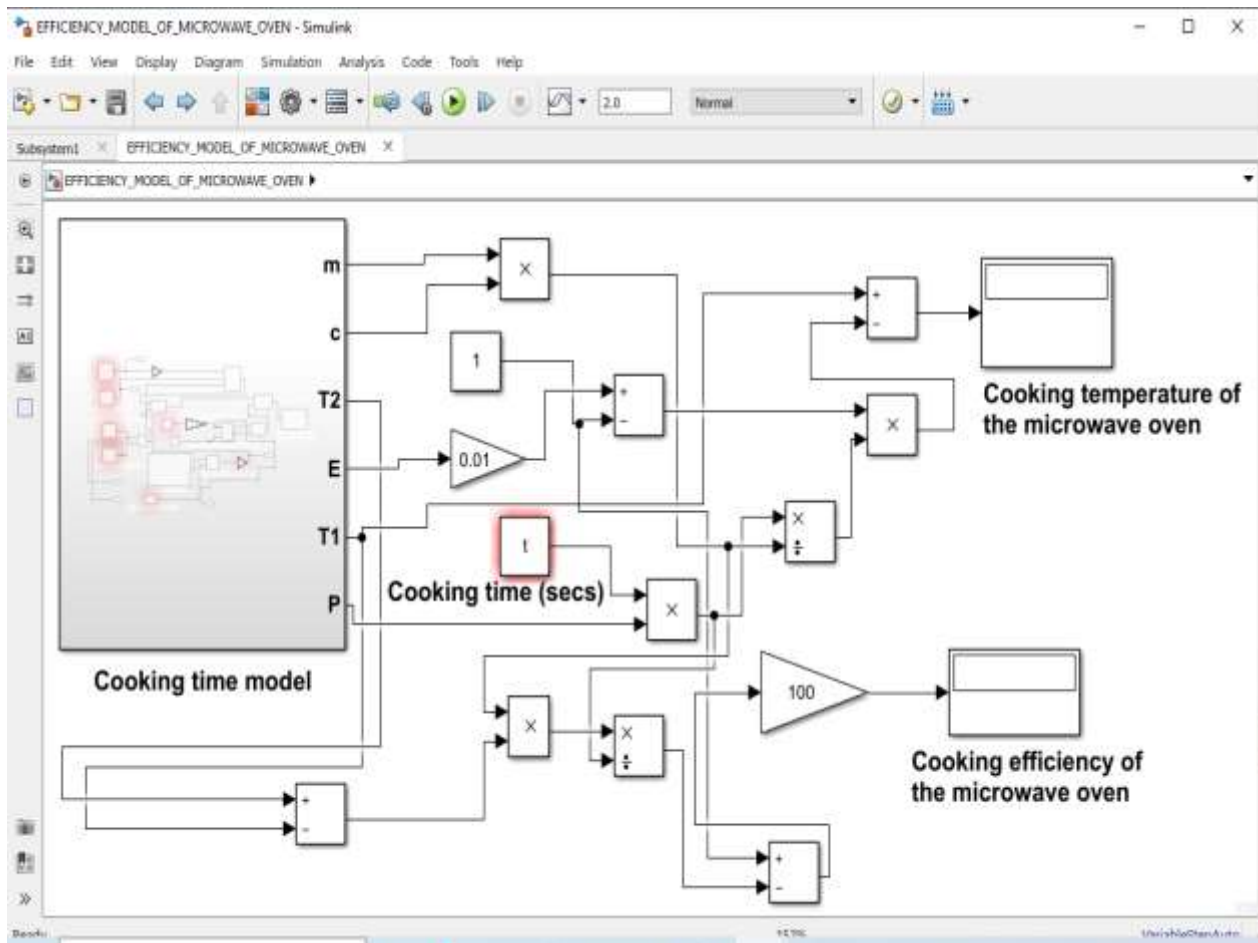


Figure 4: Cooking Temperature and Efficiency model of the microwave oven

3) 3.3 Design and Training of a Function Fitting Neural Network (FFNN) for the purpose of priming the magnetron's cathode using the neural fitting toolbox of Simulink.

In this step, a function fitting neural network was designed and trained for the purpose of priming the cathode of the A6 relativistic magnetron. The inputs to the ANN were first determined and mapped to the desired output. The cooking temperature of the microwave oven and the fluctuating power are the two inputs to the ANN. The inputs were mapped to the output in such a manner that cathode priming can be achieved.

The cathode area is the output or target for the ANN. The ANN was trained in such a way that when it receives input, it gives output based on its defined target. The ANN was trained with 324 input data which was first designed in Excel and later imported into the Neural fitting tool of Matlab. Similarly, the output training data for the neural network was also designed and presented in Excel. Just like the input data, the output data was also obtained from the input/output mapping of the magnetron parameters from the input/output mapping table. The designed input and output training data was imported into the Neural fitting tool and presented accordingly.

The training of the neural network was done using 10 neurons (Figure 5) and also using different algorithms but it was later discovered that the training with Bayesian regularization algorithm (Figure 5) converged faster and gave the best solutions for the neural network.

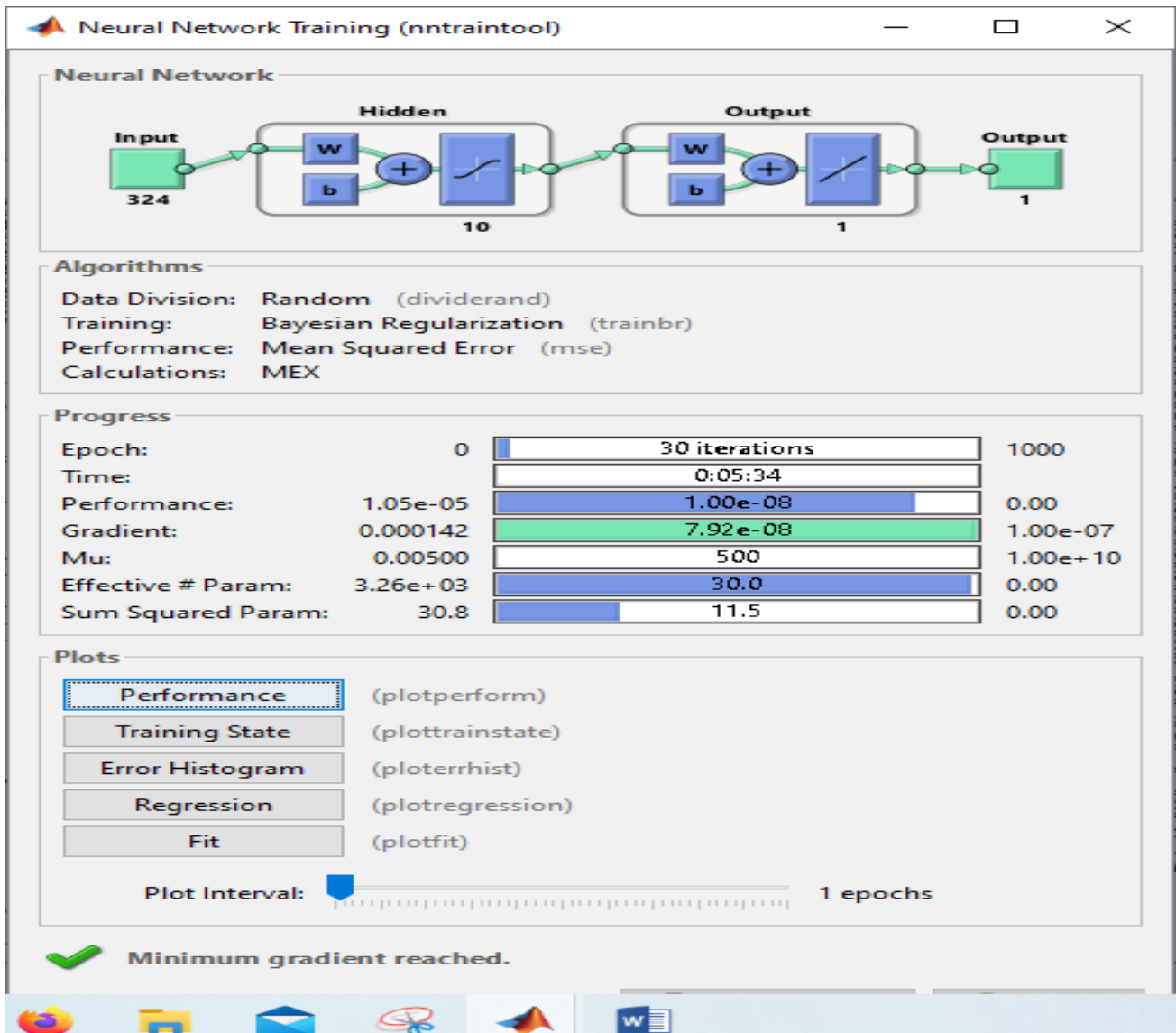


Figure 5: Trained Network

The trained neural network is shown in Figure 5. The training results were analyzed accordingly. The Matlab program for training the neural network was generated and saved appropriately.

The designed function fitting neural network was also generated and saved for the purpose of deployment. The FFNN was deployed to prime the cathode of the A6 relativistic magnetron. When cooking temperature and fluctuating power of the microwave oven comes into the ANN through its input, then based on the training it received, the FFNN recognizes the data and switches the desired output or target data in order to achieve cathode priming.

4) 3.4 Deployment of trained FFNN to the Simulink model of the A6 Relativistic magnetron for improving the efficiency of the Panasonic microwave oven

The integration of the developed model of Panasonic microwave oven with the FFNN based system was accomplished in two major steps. The first step involves the integration of the A6 magnetron with the FFNN Simulink model.

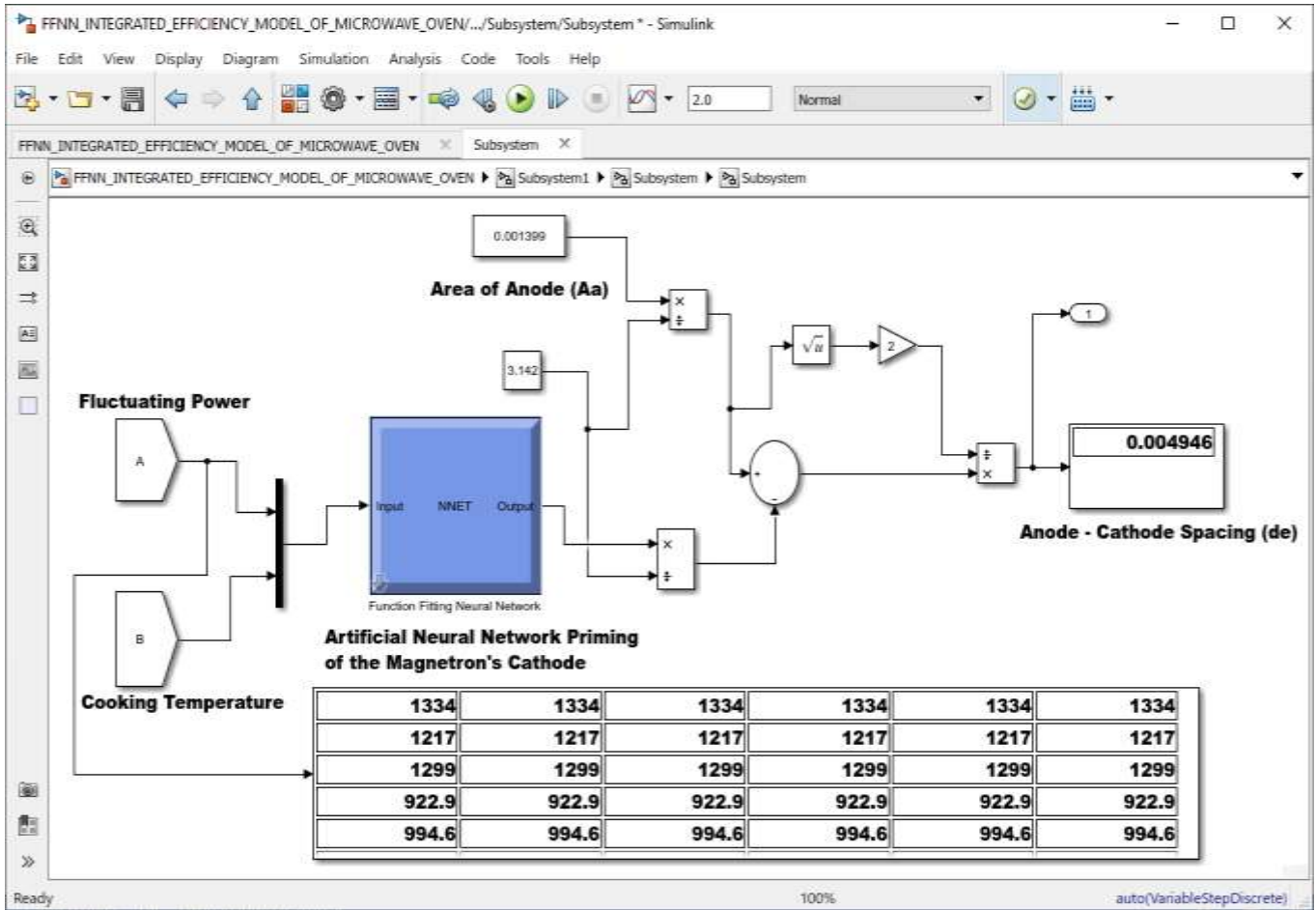


Figure 6: FFNN deployed to the A6 Relativistic Magnetron Model

This was done by replacing the area of cathode in the model of the magnetron with the developed FFNN circuit. The second stage of the integration as shown in Figure 6 involves the replacement of the anode-cathode gap block of the magnetron model with the subsystem of the generated trained network.

IV. 4. Results

Figure 7 shows the comparison chart of the Panasonic microwave oven cooking time model without/with the FFNN based cathode primed A6 relativistic magnetron integrated. The chart proved that the improved model was able to reduce the overall cooking time of the Panasonic microwave oven during the power fluctuation issue. Thus the percentage reduction in the overall cooking time during the power fluctuations is calculated as;

$$\% \text{ Reduction in overall cooking time} = \frac{t_{\text{Conventional}} - t_{\text{Improved}}}{t_{\text{Conventional}}} \times 100\%$$

$$\% \text{ Reduction in overall cooking time} = \frac{6469.05 - 6061.32}{6469.05} \times 100 = 6.3028\%$$

Figure 8 shows the comparison of the results of simulating the developed cooking temperature model of the Panasonic microwave oven without/with the FFNN based cathode primed A6 relativistic magnetron integrated. As can be observed from the chart, the cooking temperature of the improved model increased significantly when compared to its conventional counterpart. Thus this increase in cooking temperature spurred the decrease in the overall cooking time of the microwave oven. The percentage increase in the cooking temperature is calculated as,

$$\% \text{ Increase in overall cooking temperature} = \frac{T_{\text{Improved}} - T_{\text{Conventional}}}{T_{\text{Improved}}} \times 100\%$$

$$\% \text{ Increase in overall cooking temperature} = \frac{1035.68 - 979.48}{1035.68} \times 100 = 5.4639\%$$

Figure 9 shows the cooking efficiency comparison results of the developed model of the Panasonic microwave oven without/with the FFNN based cathode primed A6 relativistic magnetron integrated. As can be observed from the chart, the cooking efficiency of the improved model also increased significantly when compared to its conventional counterpart. Thus the increase in cooking temperature spurred the decrease in the overall cooking time and thereby increasing the overall cooking efficiency of the microwave oven. The percentage increase in the cooking efficiency is calculated as,

$$\% \text{ Increase in overall cooking efficiency} = \frac{\eta_{\text{Improved}} - \eta_{\text{Conventional}}}{\eta_{\text{Improved}}} \times 100\%$$

$$\% \text{ Increase in overall cooking efficiency} = \frac{36.28 - 31.99}{36.28} \times 100 = 11.82\%$$

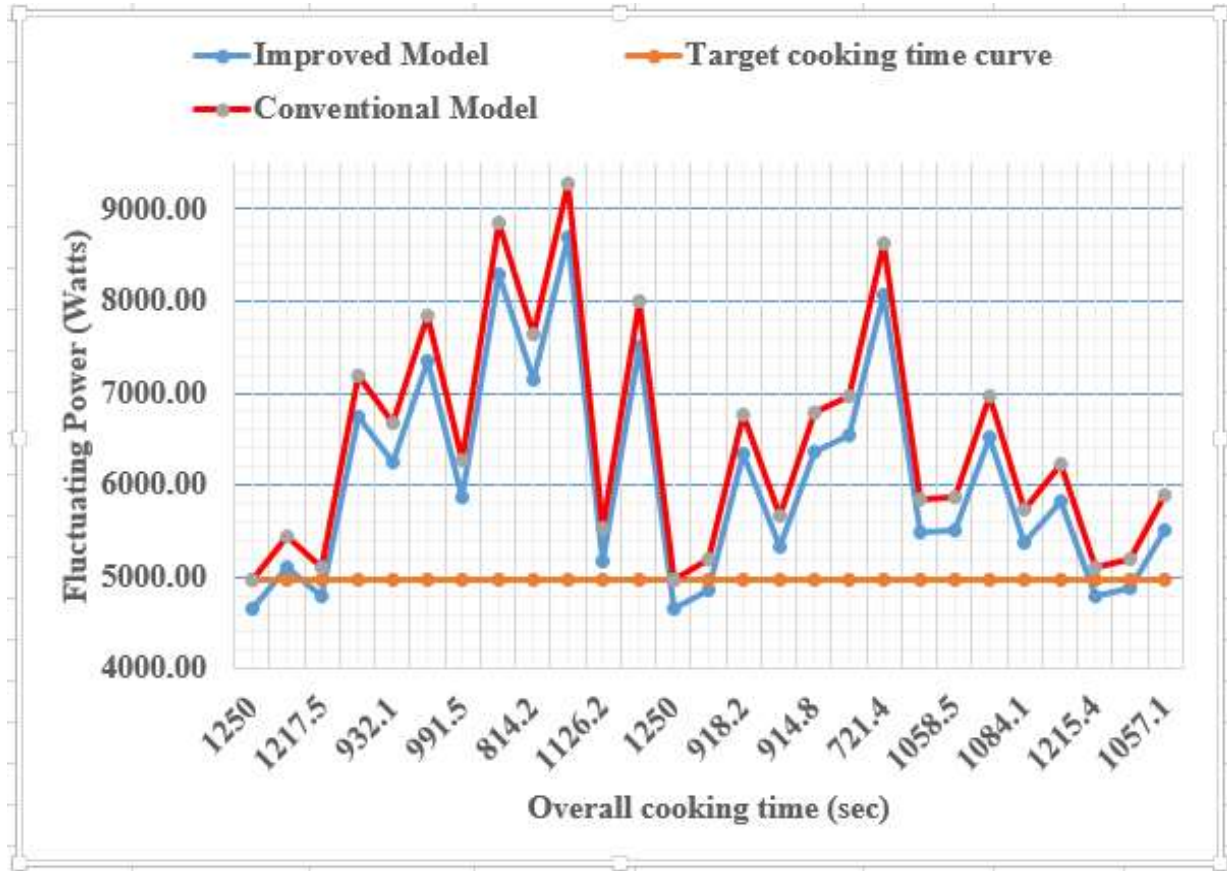


Figure 7: Cooking time comparison of the conventional and improved model

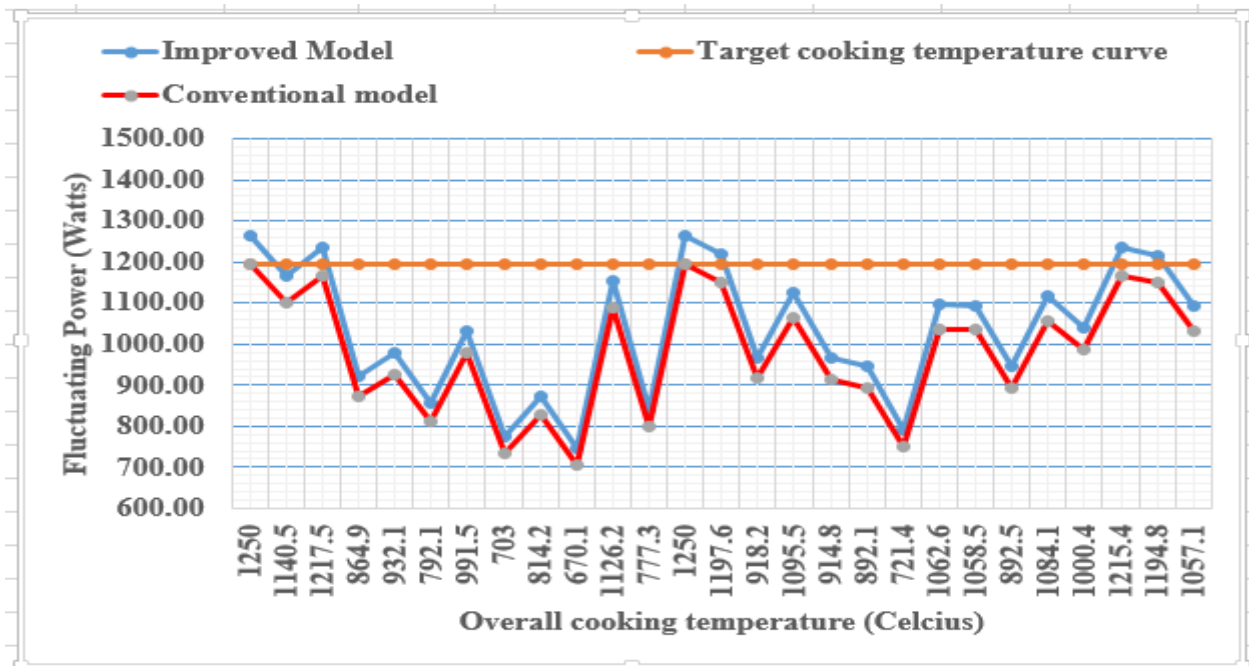


Figure 8: Cooking temperature comparison of the conventional and improved model

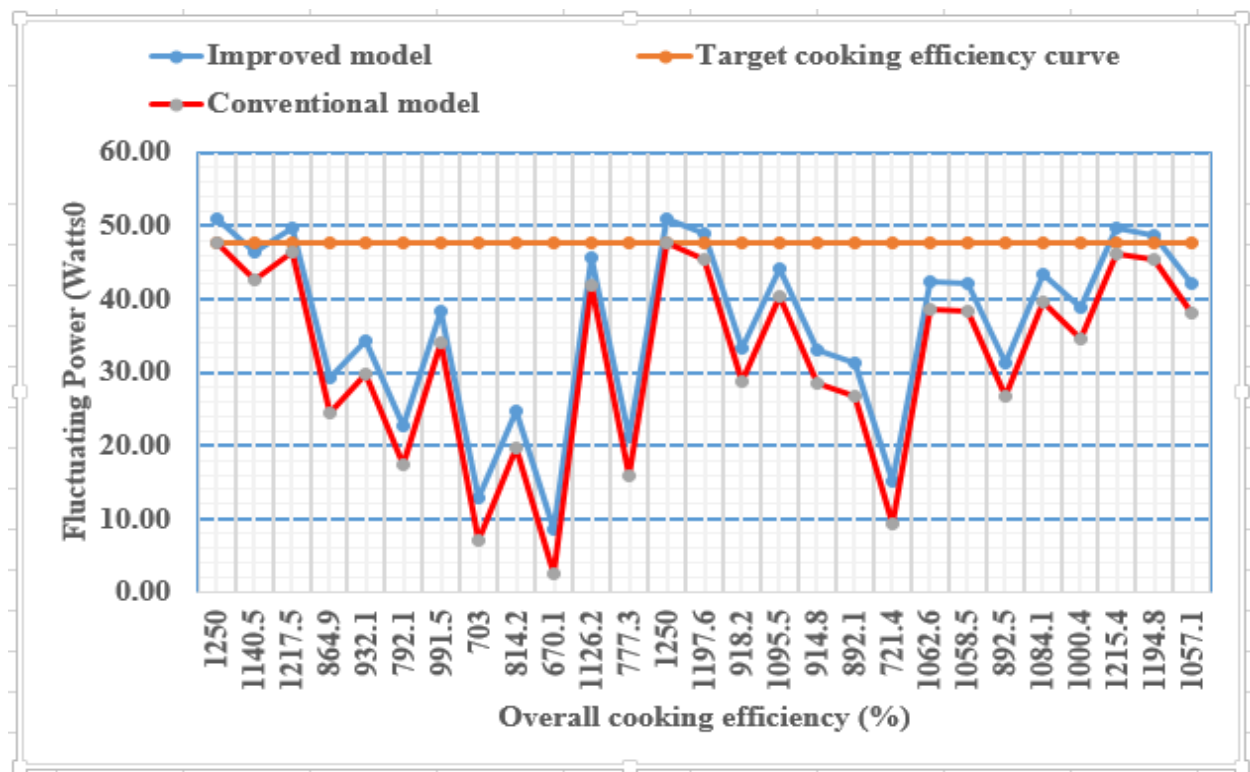


Figure 9: Cooking efficiency comparison of the conventional and improved model

V. 5. Conclusion

This paper investigated how an FFNN based cathode primed A6 relativistic magnetron can be used to improve the efficiency of microwave heating systems. The microwave heating system used for the analysis is the microwave oven and the type of microwave oven used for the analysis is the Panasonic microwave oven (model NN-SN966S). The parameters of the microwave magnetron was optimized in such a way that its overall cooking temperature was increased with the integration of the FFNN based cathode primed A6 relativistic magnetron. The increase in overall cooking temperature resulted in reduction in the overall cooking time of the microwave oven and thereby increasing its overall efficiency. The overall cooking time, cooking temperature and cooking efficiency of the conventional model was found to be 6469.05s, 979.48°C, and 31.99% respectively. Similarly, the overall cooking time, overall cooking temperature and overall cooking efficiency of the improved model was found to be 6061.32s, 1035.68°C, and 36.28% respectively. This indicates a 6.3028% decrease in cooking time, 5.4639% increase in cooking temperature and 11.82% improvement in the overall efficiency of the system. With this findings of the research, it can be concluded that the FFNN based cathode primed A6 relativistic magnetron is capable of improving the efficiency of microwave heating systems by approximately 12%.

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