OPTIMIZATION OF MICROWAVE -HALOGEN LAMP BAKING OF BREAD

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ABSTRACT

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The main objective of this study was to optimize the processing conditions of breads baked in halogen lamp-microwave combination oven by using response surface methodology. It was also aimed to construct neural network models for the prediction of quality parameters of bread as a function of processing conditions.

Different baking time and power combinations were used in order to find the optimum baking conditions of bread in halogen lamp-microwave combination oven. The independent variables were the baking time (4, 4.5, 5, 5.5, and 6 min), power of upper and lower halogen lamps (40, 50, 60, 70, and 80%), and power of the microwave (20, 30, 40, 50, and 60%). As control, breads baked in conventional oven at 200ºC for 13 min were used. The measured quality parameters were the weight loss, color change, specific volume, porosity, and texture profile of the breads. Baking time, upper halogen lamp power, and microwave power were found to be significant on affecting most of the quality parameters. On the other hand, lower halogen lamp power was found to be an insignificant factor for all of the responses.

For the optimization process, Response Surface Methodology (RSM) was used. The optimum baking conditions were determined as 5 min of baking time at 70% upper halogen lamp power, 50% lower halogen lamp power, and 20% microwave power. Breads baked at the optimum condition had comparable quality with conventionally baked ones. When halogen lamp-microwave combination oven was used, conventional baking time of breads was reduced by 60%.

Artificial neural network models were developed for each of the quality parameters in order to observe the effects of the baking time and different oven conditions on the quality of the breads. High regression coefficients were calculated between the experimental data and predicted values showing that this method is capable in predicting quality parameters of breads during halogen lamp-microwave combination baking. In addition, the results were comparable to the RSM study.

Keywords: Baking, Bread, Microwave, Halogen lamp, Optimization, Response Surface Methodology, Neural Network

ÖZ

MİKRODALGA-HALOJEN LAMBA İLE EKMEK PİŞİRİLMESİNİN OPTİMİZASYONU

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Çalışmanın ana amacı, halojen lambası-mikrodalga kombinasyonlu fırında pişirilen ekmeğin optimum pişirilme koşullarının yanıt yüzey metodu ile bulunmasıdır. Çalışmanın diğer bir amacı ise sinir ağları yapılandırılması ile ekmeğin pişirilme koşullarının ekmeğin kalite parametreleri üzerindeki etkisinin tahmin edilerek model oluşturulmasıdır.

Optimum pişirme koşulunu bulabilmek için halojen lambası-mikrodalga kombinasyonlu fırında farklı pişirme zamanları ve fırın güçleri kombinasyonları

kullanılmıştır. Bağımsız değişkenler; pişirme zamanı (4, 4,5, 5, 5,5, 6 dakika), alt ve üst halojen lambalarının güçleri (% 40, 50, 60, 70, 80) ve mikrodalga gücüdür (% 20, 30, 40, 50, 60). Kontrol olarak konvansiyonel fırında 200˚C'da 13 dakika pişirilen ekmekler kullanılmıştır. Ölçülen kalite parametreleri ise, ekmeklerin ağırlık kaybı, rengi, özgül hacmi, gözenekliliği ve tekstürel yapılarıdır. Pişirme zamanı, üst halojen lambalarının gücü ve mikrodalganın gücü birçok kalite parametrelerinde etkili bulunmuştur. Buna karşın, alt halojen lambasının gücünün bütün kalite parametrelerinde etkisiz olduğu gözlenmiştir.

Optimizasyon işlemi için yanıt yüzey metodu kullanılmıştır. Halojen lambası-mikrodalga kombinasyonlu fırında optimum pişirme koşulları, %20 mikrodalga gücü, %70 üst halogen lambaların gücü, %50 alt halojen lambasının gücü ile 5 dakika olarak belirlenmiştir. Kombinasyonlu fırında, belirlenen optimum koşullarda pişirilen ekmeklerin kaliteleri konvansiyonel fırında pişirilen ekmekler ile karşılaştırılabilir düzeyde olmuştur. Halojen lambası-mikrodalga kombinasyonlu fırında ekmek pişirildiğinde, pişirme zamanı konvansiyonel fırına göre %60 azalmıştır.

Pişirme zamanının ve farklı fırın koşullarının her bir kalite parametresinin üzerindeki etkilerini gözlemleyebilmek için yapay sinirsel ağ modelleri kurulmuştur. Deneysel veri ve yapay ağ yöntemi ile hesaplanan veri arasında belirlenen yüksek regresyon katsayıları bu metodun halojen lambası-mikrodalga kombinasyonlu fırında pişirilen ekmeklerin kalite parametrelerinin tahmin edilmesinde başarılı olduğunu göstermektedir. Aynı zamanda elde edilen sonuçlar yanıt yüzey yöntemi ile elde edilen sonuçlarla karşılaştırılabilir düzeydedir.

Anahtar sözcükler: Pişirme, Ekmek, Mikrodalga, Halojen lamba, Optimizasyon, Yanıt Yüzey Metodu, Sinirsel Ağ.

Dedicated to my mother and father…

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INTRODUCTION

1.1 Bread Baking

Bread is considered to be one of the oldest 'processed' food by the humanity. In its earliest forms bread would have been very different from how we see it in industrialized countries today and it would probably be closest in character to the modern flat breads of the Middle East (Cauvain, 1999).

Today, the bread making process is mainly based on 3 steps: dough formation, fermentation, and baking.

Dough formation requires the mixing of flour, water, yeast, salt and other ingredients depending on the bread type in appropriate ratios. Dough development is a relatively undefined term, which covers complex changes in bread ingredients, which are set in motion when the ingredients first become mixed. The changes are associated with the formation of gluten, which requires both the hydration of the proteins in the flour and the application of energy through the process of kneading. Kneading is the development of gluten structure in the dough through the application of energy during mixing (Cauvain, 1999). Mixing the dough provides two functions: homogeneous distribution of components, and development of the gluten matrix. Gluten is the skeleton of wheat-flour dough and responsible for gas retention which provides the production of light loaf of bread. Mixing time varies with the flour, dough temperature, dough consistency, and mixer. Excessive mixing yield a dough with reduced elasticity and extensibility (Pomeranz and Shellenberger, 1971).

During the fermentation process, gas is generated as a part of the metabolic activity of yeast. Many microorganisms can ferment sugars with the production of carbon dioxide, but the organism that seems to function best in dough is *Saccharomyces cerevisiae* or bakers' yeast. Every live yeast cell can perform many different chemical reactions, but those of most importance are in the group called fermentation. The most obvious manifestation of these changes is the production of carbon dioxide and ethyl alcohol, but these substances are merely the end result of an extremely complex series of reactions that are largely controlled by enzymes. Sugars are the substrates transformed by fermentation (Matz, 1992). A simplified equation that describes the substrate and principle end products of the fermentation reactions is:

$$C_6H_{12}O_6 \longrightarrow 2C_2H_5OH + 2CO_2$$

Carbon dioxide is responsible for leavening the dough, while ethyl alcohol helps to make up the complex aroma of the baked products. A large part of these compounds is lost during the baking and the cooling stages (Matz, 1992). In yeast leavened doughs, the products of microbial metabolism modify the dough and are essential for production of light, well-aerated, and appetizing bread (Pomeranz and Shellenberger, 1971).

Duration of the fermentation process depends on the amount and the quality of the ingredients. Yeast is the most important ingredient that affects the fermentation process. The relationship between dough development time and yeast level probably comes from the contribution that enzymes present in the yeast cells, viable or dead. They modify the protein structures, which are forming with increasing dough resting time. Of the enzymes present, the proteolytic enzymes and the natural reducing agent glutathione are likely to play the major roles. Flour also contains enzymes, which can contribute to dough development. Since the mechanism for dough development in fermentation depends on yeast activity, the temperature of the dough play a major role in determining the time at which full development is achieved (Cauvain, 1999).

During baking several changes take place both in the crumb and crust. The browning reaction that involves both caramelization of sugars and proteinaceous materials imparts a deep color to the crust. Thermal decomposition of starch and formation of dextrins contribute to crust brightness. This is accompanied by formation of flavor and taste components. At the same time changes take place inside the loaf of bread. At early stages the increase in temperature enhances enzymatic activity and growth of yeast and bacteria. At about 50ºC-60ºC the yeast and bacteria are killed. Above that temperature starch gelatinizes, proteins coagulate, and enzymes are inactivated. Steam is formed at around 100ºC, at which the final volume and crumb texture of the bread are set. The inside of the loaf does not exceed 100ºC; however, in the crust much higher temperatures are attained. In the temperature range of 100-150ºC, light and brown dextrins are formed which are followed by caramel (Pomeranz, 1987).

In addition to conventional baking there are different methods to bake breads which are, microwave baking (Lorenz et al., 1973; Tsen, 1980; Sumnu, et al., 1999; Ozmutlu, et al., 2001), conventional baking combined with microwave baking (Willyard, 1998), combination of impingement and microwave baking (Ovadia and Walker, 1995), near infrared baking (Wade, 1987; Ginzburg, 1969). In this study, since halogen lamp-microwave combination oven was used, first, the microwave heating mechanism and microwave baking then, halogen lamp heating mechanism and halogen lamp baking will be discussed.

1.2 Microwave Heating

Microwave heating has been applied to the processing of food products since 1950s. The earliest example of a successful process is the drying of potato chips (Shiffmann, 1986).

In microwave processing it is important to recognize that microwaves are a form of energy, not a form of heat, and are only manifested as heat upon interaction with a material as a result of one or more energy transfer mechanisms (Shiffmann, 1986). Microwaves are electromagnetic waves of radiant energy and have wavelengths between radio and infrared waves on the electromagnetic spectrum. Microwaves radiate outward from a source and can be absorbed, transmitted, and reflected (Giese, 1992). Microwaves used in the food industry for heating are 2450 MHz or 915 MHz, corresponding to 12 cm or 34 cm in wavelength (Ohlsson and Bengtsson, 2002).

The majority of foods contain a substantial proportion of water. The molecular structure of water consists of negatively charged oxygen atom, separated from positively charged hydrogen atoms, which forms an electric dipole. When microwave is applied to a food, dipoles in the water attempt to orient themselves to the field. Since the rapidly oscillating electric field changes from positive to negative and back again several million times per second, the dipoles attempt to follow and these rapid reversals create frictional heat. The increase in temperature of water molecules heats surrounding components of the food by conduction and/or convection. In microwave heating the outer parts of the food sample receive the same energy as inner parts, but the surface loses its heat faster to the surroundings by evaporative cooling. It is the distribution of water within a food that has the major effect on the amount of heating, although differences also occur in the rate of heating as a result of the shape of the food (Ohlsson and Bengtsson, 2002). In addition, most of the food products contain dissolved salts such as sodium, potassium, and calcium chlorides. When these salts dissolve, the molecule ionizes or separates into two charged particles or ions. Under the influence of the microwave electric field, these ions oscillate back and forth and they collide with their neighboring atoms or molecules. These collisions impart agitation or motion, which is defined as heat. Materials with mobile ions are conductive, in that the movement or flow of charged particles is defined as the conduction of electricity. The more available conducting ions a material has the higher is its electrical conductivity. Since the microwave absorption of a material depends on the number of ions it can interact with, the microwave absorption of such a material increases with its conductivity (Buffler, 1993).

The fundamental equation for microwave power absorption by a material is expressed as:

$$P_v = 2\pi\ f\varepsilon_0\varepsilon'' E^2 \qquad (1.1)$$

where, P_v is the power absorbed per unit volume (W/m^3), f is the frequency of the microwave system (Hz), E is the electric field inside the load (V/m), ε_0 is the permitivity of free space (F/m) and ε'' is the dielectric loss factor for the food sample (Buffler, 1993).

The heating of materials by microwaves is affected by a number of properties of the oven and the material being heated.

The most important property of the oven is its frequency. The frequency effects the penetration depth, which is defined as the depth at which the magnitude of the field has been decreased to 1/e (36.8%) of its value at the surface of the material **(**Dibben, 2001). Therefore, the selection of the microwave frequency is important, as it is related to the size of the object being heated. Frequency has another role, since the dielectric properties of the material are affected by it. However, this effect is often of lesser importance in food systems, where the complexity of the chemical makeup and other heat mechanisms are overriding factors (Shiffmann, 1986). The dielectric properties are the dielectric constant, which represents the ability of a food to store electrical energy, and dielectric loss factor, which describes how well a material absorbs the microwave fields passing through it and converts into heat. The dielectric properties of foods are dependent on the content of moisture and salt (Giese, 1992).

The physical properties of the food samples that affect the microwave heating are the physical geometry (size and shape), mass, moisture content, temperature, density, specific heat, and thermal conductivity of the food material. If the size of the food material is very large in comparison to the depth of penetration, the heating will not be uniform. If the shape is regular, uniform heating will be observed. Sharp edges and corners should be avoided, since these will tend to overheat. For the total mass of the food sample, there is a direct relationship between the mass and the amount of microwave power. Usually, the higher the moisture content, the higher the dielectric loss factor and hence, the better the heating. At very low moisture level, the water is bound and not free to be affected by the rapidly alternating microwave field. The temperature of a food affects both dielectric properties and final temperature achieved. The density of a product has an effect upon its dielectric constant. Specific heat capacity can cause a material, which has relatively low dielectric loss to heat well in a microwave field. Thermal conductivity has an important effect when heating the large materials where the depth of penetration is not great enough to heat uniformly to the center, or when the microwave heating time is long (Shiffmann, 1986).

Microwave processing have several advantages when compared to conventional heating methods such as, speed of operation, energy savings, precise process control, and faster start-up and shut-down times (Decareau, 1985).

There are various industrial applications of microwave heating like tempering, drying, cooking, sterilization and pasteurization, enzyme inactivation, and baking (Giese, 1992).

1.3 Microwave Baking

Microwave energy was first suggested for use in the baking industry in 1947 for preservation of baked products (Lorenz et al., 1973). Since 1960s, much research has been carried out to study the effects on baked products of microwave ovens in comparison with conventional ovens (Yin and Walker, 1995). Bread baking by means of microwave energy was first reported in literature in 1966 (Shiffmann, 2001).

The most important problem in microwave baking is the lack of browning. The browning problem is due to the ambient temperature in the microwave oven since it rarely reaches much above the room temperature. Evaporative cooling occurs at the surface of foods cooked by microwaves and the result is a negative temperature gradient; that is, a higher temperature inside the food than at the surface. Thus, the two factors responsible for browning to occur are essentially absent: time and temperature (Decareau, 1992). To summarize, in microwave baking there is internal heat generation and therefore heating rate is very rapid. Microwave energy is distributed throughout the dough piece, and the oven is at ambient temperature. Consequently, the surface temperature of the dough is not high enough to promote browning and crust formation (Willyard, 1998). Lorenz et al. (1973) studied the baking of relatively dark bakery products, which crust formation is not very important, by microwave energy, using specially designed and manufactured plastic baking pans. In order to overcome the browning problem, combined systems were used. Willyard (1998) studied the microwave baking in combination with conventional browning in the production of hot-dog buns and concluded that 4.5 min of conventional browning at 232ºC followed by 50 sec of microwave baking produced the best result. Sahin et al. (2002) studied the effects of susceptor, coating and conventional browning applications on color and crust formation during microwave baking. According to their research, susceptors and conventional browning were found to be successful in obtaining sufficient color and crispness at the bottom surface but coating was found to be not effective, so, not advisable in microwave baking.

The short baking times and low temperatures in the microwave oven also prevents the flavor development. Flavor systems designed to work in a conventional product, however, often produce unacceptable results when microwave is used. Microwave heating causes different flavor components to flash off at different rates and in different proportions than they would under regular heat. Moreover, different reactions take place in the microwave, resulting in different outcomes (Hegenbert, 1992). Susceptor packaging was used to solve this problem. However, the problem was solved only at the surface where susceptors are applied (Whorton and Reinecclus, 1990).

In microwave baking, the moisture transport mechanism is different than the conventional baking. In conventional ovens, the surrounding medium (typically air) is at very high temperatures. The moisture evaporates from the surface and a drier, porous region develops, which has a lower thermal conductivity. This provides a temperature drop from surface to the interior. The moisture of the surface decreases quickly at high temperatures while moisture from inside diffuses to the surface to be convected away. Although high internal temperatures produce some internal evaporation, internal pressures are small and pressure-driven flow of liquid vapor is not as significant as microwave heating. However in microwave ovens, higher rates of internal evaporation which results pressure generation modify the moisture transport considerably. As the air temperature inside the microwave oven is cold, the moisture removal capacity of the air is drastically reduced which results in soggy products (Datta, 2001). Most studies in literature indicate a significantly greater moisture loss in foods cooked by microwave energy than other cooking methods due to the positive pressure gradient toward the food surface, which are coupled with the low vapor pressure surrounding the product (Decareau, 1992). Breads and cakes baked in microwave oven were also shown to have higher moisture losses as compared to conventionally baked ones (Sumnu et al., 1999; Sahin et al., 2002; Keskin et al., 2004a).

Microwave baking has another problem of unacceptable texture. The exteriors are rubbery, leathery, tough, and difficult to tear, and the interiors are firm and difficult to chew (Shukla, 1993). Dough has two polymeric materials gluten protein and partially gelatinized starch. This starch is still largely granular but becomes embedded in the gluten network. The firmness problem of the bread interior is usually associated with the large diameter, re-swollen starch granules. The size of gelatinized granules can be reduced by incorporating fats and emulsifiers that delay gelatinization (Shukla, 1993). Ozmutlu et al. (2001) studied the effects of different amounts of gluten, fat, emulsifier, and dextrose on the quality of breads baked in microwave oven. Firmness of breads was found to be reduced when low gluten flour was used and as fat and emulsifier contents increased. Toughness is related to gluten protein. The gluten proteins can be reduced by breaking the disulfide bonds. Enzymes such as protease and deaminase can be used for this purpose (Shukla, 1993). Keskin et al. (2004b) studied the effects of different enzymes which are, α-amylase, xylanase, lipase, and protease, on the quality of breads baked in conventional, microwave, and halogen lamp-microwave combination oven. The enzymes were found to be effective on reducing the firmness in microwave and halogen lamp-microwave combination oven.

Rapid staling is another disadvantage of microwave baking. The staling mechanism of microwave baked products is still unclear. According to Higo's effect hypothesis, when bread is heated by microwaves, more amylose is leached out the of starch granules. This amylose was found to be more disoriented and contained less bound water than in conventionally heated bread. Upon cooling, the surrounding amylose molecules align and contribute to crumb firmness. With microwave-heated bread, amylose is better able to realign into a more crystalline structure than conventionally heated bread and become harder very rapidly (Ovadia, 1994). Seyhun et al. (2003) studied the effects of different types of emulsifiers, gums, and fat contents on the retardation of staling of microwave baked cakes. The use of emulsifiers, gums, and fat content were found to be effective on the retardation of staling in microwave baking.

Although there are many studies to improve the quality of the microwave baked products, additional studies should be performed in order to obtain the same quality of bakery products as in conventional oven.

1.4 Halogen Lamp Baking

Infrared is usually divided into 3 spectral regions: near, mid and far-infrared. Infrared light lies between the visible and microwave portions of the electromagnetic spectrum. Infrared waves have a frequency range of $3*10^{11} – 4*10^{14}$ Hz. Near infrared light is closest in wavelength to visible light and far infrared is closer to the microwave region of the electromagnetic spectrum.

Halogen lamp heating provides near infrared radiation and has a wavelength range of 1 – 5 µm. When infrared waves strike a material, they are either reflected, transmitted or absorbed. Absorbed waves are transformed into heat and the temperature of the material increases (Ohlsson and Bengtsson, 2002).

Near infrared radiation provides to reach the working temperatures in seconds while offering rapid transfer of high amounts of energy and excellent process control. Near infrared has a penetration depth of several millimeters in many foods and can therefore be used to about the same effect as microwaves or high frequency for thin materials (Ohlsson and Bengtsson, 2002).

In order to overcome the sogginess problem occurring in microwave heating, Datta and Ni (2002) worked on infrared and hot-air assisted microwave heating. They mentioned that the infrared penetration depth had a strong influence on how much the surface temperature increases or the level of moisture that builds up over time. They also showed that the largest increase in surface temperature occurs for zero infrared penetration depth (all absorbed on surface). Therefore, zero penetration depth corresponded to the lowest surface moisture.

The main commercial applications of infrared heating are drying of low moisture foods such as breadcrumbs, flour, grains, malt, and tea. It is also used as an initial heating stage to speed up the initial increase in surface temperature. In this role it is used in baking and roasting ovens and in frying as well as drying. Infrared heating has also been used for thawing and pasteurization of packaging materials (Ohlsson and Bengtsson, 2002).

The main advantages of using near infrared heating are high and effective heat transfer, reduction of baking time, no heating of air in the oven, quick regulation and control, and compact and flexible ovens (Ohlsson and Bengtsson, 2002).

The baking of pastry, biscuits, and breads by near infrared radiation has been studied by Ginzburg (1969), Wade (1987) and Keskin et al. (2004a).

The near infrared baking provided to reduce the baking time about 25-50% compared to an ordinary baking oven depending on the thickness of the product (Ohlsson and Bengtsson, 2002). However, increase in power increased the weight loss of the breads. Halogen lamp power was found to be insignificant on the firmness but significant on specific volume of the breads (Keskin et al., 2004a). As halogen lamp power increased, specific volume of breads was found to increase. The most important advantage of the halogen lamp heating was the achievement of browning at the surface of the breads in shorter time.

1.5 Halogen Lamp-Microwave Combination Baking

Halogen lamp-microwave baking is a new technology, which is the combination of microwave heating and halogen lamp heating. The use of halogen lamp-microwave combination oven combines the time saving advantage of microwave and crust and color formation advantage of the halogen lamps. The studies on halogen lamp-microwave combination baking are limited in literature. Keskin et al. (2004a) studied the effects of halogen lamps and microwave on weight loss, firmness, specific volume, and color development of breads. Firmness and weight loss were found to be higher when compared with conventional baking. So, in order to improve the quality of the breads, different enzymes were used and as a result the firmness was found to be decreased.

1.6 Response Surface Methodology

Response Surface Methodology (RSM) is a collection of statistical and mathematical techniques useful for developing, improving, and optimizing processes. It also has important applications in the design, development, and formulation of new products, as well as in the improvement of existing product design (Myers and Montgomery, 2002).

The most extensive applications of RSM are in the industrial world, particularly in situations where several input variables potentially influence some performance measure or quality characteristic is called the **response**. It is typically measured on a continuous scale, although attribute responses, ranks, and sensory responses are not unusual. Most real-world applications of RSM will involve more than one response. The input variables are sometimes called **independent variables**, and they are subject to the control of the engineer or scientist, at least for purposes of a test or an experiment (Myers and Montgomery, 2002).

Basically RSM is a four-step process. First, the critical factors that are important to the product or process under study are identified. Second, the range of factor levels which will encompass the physical specifications of the samples are defined. Third, the specific test samples are determined by the experimental design and then tested. Fourth, the data from these experiments are analyzed by RSM and then interpreted.

There are five assumptions in order to use RSM effectively:

1. The factors, which are critical to the product, are known.
2. The region of interest where the factor levels influence the product is known.
3. The factors vary continuously throughout the experimental range tested.
4. There exists a mathematical function that relates the factors to the measured response.
5. The response, which is defined by this function, is a smooth surface.

In addition to these assumptions, the experimenter should be aware of five limitations when using RSM:

1. Large variation in the factors can result in misleading conclusions.
2. The critical factors of the product may not be correctly specified or sufficiently defined resulting in an inaccurate description of the optimum product.
3. The optimum product may not be determined by RSM because the range of factor levels tested was too narrow or too broad to specify the optimum.
4. As with any experiment, biased results can occur if good statistical principles are not followed.
5. Over-reliance on the computer to conduct the experiment can lead to incomplete results. The experimenter must use good judgement and knowledge about the product to draw appropriate conclusions from the data.

As a summary, RSM is a statistical technique that uses quantitative data to determine and simultaneously solve multivariate equations, which specify the optimum product for a specified set of factors through mathematical models. These models consider interactions among the test factors and can be used to determine how the product changes with changes in the factor levels. RSM is more efficient than traditional experimental procedures because it decreases the time and cost required to determine the optimum product (Giovanni, 1983).

Response Surface Methodology was applied to baking studies for optimization. Willyard (1998) used RSM to study the effects of water absorption, mixing time, gluten level and oxidation for conventional baking and conventional browning-microwave baking. Also, in the same study, the effects of yeast level, fermentation time, and proof time on conventional browning-microwave baking were investigated by using RSM. Lahtinen et al. (1998) studied the dependence of cake firmness and cake moisture content on initial fat temperature, mixing intensity, mixing time, mass ratio of fat and sucrose, and storage by using RSM. The effects of hydrocolloids added singly and in association at different levels, on the investigated rheological, mechanical, and thermal properties of wheat bread dough were evaluated by RSM by Collar et al. (1999). Sumnu et al. (2000) studied the effects of water content, emulsifier content, baking time, microwave oven power, shortening content, and starch type on specific gravity of batter and volume index, uniformity index, and tenderness of the crumb for microwave baked cakes by using RSM. The processing conditions in halogen lamp-microwave combination oven have not been optimized yet. Therefore, in this study the baking conditions in halogen lamp-microwave combination oven were optimized by RSM so that the quality of breads in this oven would be comparable with that of breads baked in conventional oven.

1.7 Neural Network

Some researchers have suggested using neural networks as an alternative to RSM (Myers and Montgomery, 2002). The development of neural networks, or more accurately **artificial neural networks** (ANN) has been motivated by the recognition that the human brain processes information in a way that is fundamentally different from the typical digital computer. The neuron is the basic structural element and information-processing module of the brain. A typical human brain has an enormous number of neurons arranged in a highly complex, nonlinear, and parallel structure. Consequently, the human brain is a very efficient structure for information processing, learning, and reasoning. An artificial neural network is a structure that is designed to solve certain types of problems by attempting to try to do as well as the way the human brain would solve the problem (Myers and Montgomery, 2002).

An artificial neural network is a mathematical algorithm which has the capability of relating the input and output parameters, learning from examples through iteration, without requiring a prior knowledge of relationships of the parameters (Torrecilla et al., 2004).

Multilayer feed-forward artificial neural networks are multivariate statistical models used to relate p predictor variables $x_1, x_2, ..., x_p$ to q response variables $y_1, y_2, ..., y_q$. The model has several **layers**, each consisting of either the original or some constructed variables. The most common structure involves three layers: the **inputs**, which are the original predictors; the **hidden layer**, consisting of a set of constructed variables; and the **output layer**, made up of the responses. Each variable in a layer is called a **node**. Figure 1.1 shows a three-layer artificial neural network. A node takes as its input a transformed linear combination of the outputs from the nodes in the layer below it. Then it sends as an output a transformation of itself that becomes one of the inputs to one or more nodes on the next layer. The transformation functions are usually either sigmoidal (S-shaped) or linear, and are usually called **activation functions** or **transfer functions** (Myers and Montgomery, 2002).

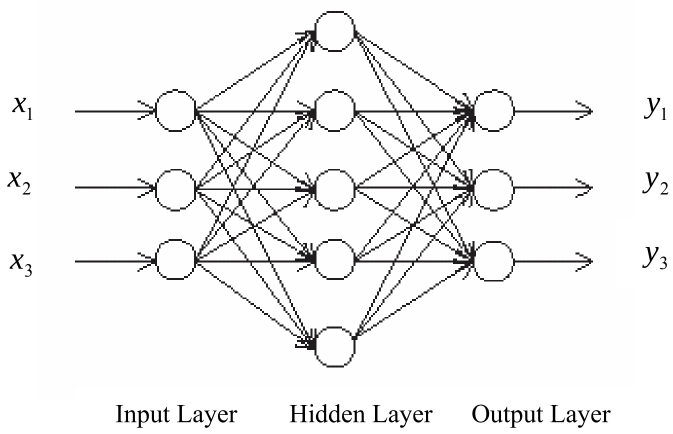


Figure 1.1 Artificial neural network with one hidden layer

A node consists of a neuron with positioning and connection information. A connection consists of a weight with node addressing information. Neurons (or cells) are single processing elements, which connected to neurons in the next layer, therefore forming different types of ANN. A parameter w_{ju} (known as weight) is associated with each connection between two cells. Thus each cell in the upper layer receives weighted inputs from each node in the layer below. The most popular ANN is the feed forward multi-layer, where the neurons are arranged into layers: input layer, hidden layer, and output layer as mentioned before, which enable the network to model non-linear and complex functions (Razavi et al., 2003).

In order to understand the algorithm of the neural network, a detailed explanation is given below.

Let each of the k hidden layer nodes a_u be a linear combination of the input variables:

$$a_u = \sum_{j=1}^{p} w_{1ju} x_j + b_u \tag{1.2}$$

where w_{1ju} are unknown parameters that must be estimated (called weights) and b_u is a parameter that plays the role of an intercept in linear regression called as the **bias node** (Myers and Montgomery, 2002). The bias neurons do not take any input and they emit a constant output value across weighted connections to the neurons in the next layer (Razavi et al., 2003).

Each node is transformed by the transfer function $g\,(\;)$. If the output of node a_u is denoted by $z_u = g(a_u)$, then a linear combination of these outputs, say $l_v = \sum_{u=0}^{k} w_{2uv} z_u$, where $z_0 = 1$. Finally, the v^{th} response y_v is a transformation of the l_v, say $y_v = \tilde{g}(l_v)$, where $\tilde{g}\,(\;)$ is the transfer function for the response. This can all be combined to give

$$y_v = \tilde{g}[\sum_{k=1}^{u} w_{2uv} g(\sum_{j=1}^{p} w_{1ju} x_j + b_{1j}) + b_{2u}] \tag{1.3}$$

The response y_v is a transformed linear combination of transformed linear combinations of the original predictors. For the hidden layer, the transfer function is often chosen to be either the logistic function or the hyperbolic tangent function. The choice of transfer function for the output layer depends on the nature of the response. The model equation 1.3 is a very flexible form containing many parameters, and this is why the neural network has a nearly universal approximation property. That is, it will fit many naturally occurring functions (Myers and Montgomery, 2002).

As mentioned before, each neuron consists of a transfer function expressing internal activation level. Output from a neuron is determined by transforming its input using a suitable transfer function. Generally, the transfer functions are sigmoidal function, hyperbolic tangent and linear function, of which the most widely used for non-linear relationship is the sigmoidal function (Razavi et al., 2003). The general form of this function is as follows:

$$f(x_j) = \frac{1}{1 + e^{-x_j}} \tag{1.4}$$

If there are so many parameters involved in a complex nonlinear function, there is considerable danger of **overfitting**. That is, a neural network will provide a nearly perfect fit to a set of historical or training data, but it will often predict new data very poorly (Myers and Montgomery, 2002).

Major benefits in using ANN are excellent management of uncertainties, noisy data and non-linear relationships. Neural network modeling has generated increasing acceptance and is an interesting method in the estimation, prediction and control of bioprocesses. ANN modeling has been successfully applied to the prediction of dough rheological properties, physical properties of ground wheat, thermal conductivity of fruits and vegetables, food quality (Sablani et al., 2002). Also there are many studies of modeling of several food processes and food quality (Farkas et al., 2000a, 2000b; Ni, Gunasekaran, 1998).

1.8 Objectives of the Study

The main objective of this study was to optimize the baking conditions in halogen lamp - microwave combination oven so that the quality of breads would be comparable with that of conventionally baked breads.

The most important problem in microwave baking is the lack of surface browning and crust formation. In addition, higher firmness values and weight loss were observed during microwave baking. It was aimed to solve these problems by using halogen lamp-microwave combination oven and to determine optimum baking condition using Response Surface Methodology (RSM). In addition, the effects of different oven parameters such as upper and lower halogen lamp power, microwave power, and baking time on the quality of the baked breads were investigated and modeled. It was also aimed to reduce the baking times by using halogen lamp-microwave combination oven when compared with conventional baking. Furthermore, the possibility of artificial neural networks in modeling the physical properties of breads during halogen lamp-microwave combination baking was evaluated and the predicted properties were compared with the results found by RSM. In recent years, computer based numerical analyses have become the main tool for understanding and predicting food processes. Neural network modeling has generated increasing acceptance and is an interesting method in the estimation and prediction of food properties and process related parameters.

Halogen lamp-microwave combination oven is a new technology and the studies about this oven are limited in literature. There is no optimization study about halogen lamp-microwave combination baking. Therefore, it was aimed to optimize the baking conditions in halogen lamp-microwave combination oven by using RSM.

CHAPTER 2

MATERIALS AND METHODS

2.1 Materials

Bread flour was supplied from Ankara Un, Turkey. Flour contains 32% wet gluten, 13.1% moisture and 0.55% ash. All the other ingredients were supplied from a local market.

2.2 Preparation of bread dough

The composition of the dough on flour basis was; 100% flour, 8% sugar, 2% salt, 6% milk powder, 3% yeast, 8% margarine, 55% water.

Before the dough preparation, the room temperature was adjusted at 26 ± 2 ^{o}C by using an air conditioner (Samsung Electronics Co., Ltd., AQ09S8GE, Korea).

Dough was prepared by using straight dough method. First, all the dry ingredients (flour, sugar, salt, and milk powder) were mixed for 1 min by a mixer at 58 rev/min (Kitchen Aid, 5K45SS, USA). Then, yeast dissolved in 30ºC water, which is the optimum temperature for the yeast cells to be activated, and melted margarine were added to the dry ingredients. All the ingredients were again mixed for 2.5 min by the help of the same mixer at 85 rev/min and during mixing, water was added to the mixture. After mixing, the dough was fermented in an incubator (Nüve EN 400, Turkey) at 30ºC with 85% relative humidity. Relative humidity was adjusted by using saturated potassium chloride solution placed at the bottom of the incubator. The humidity was controlled by a hygrometer (Nel RH 1300, Turkey). The total fermentation time was 105 min. After the first 70 min, the dough was punched to remove the carbon dioxide and again placed into the incubator. The second punch took place after 35 min. Then, the dough was divided into 50 g pieces and shaped. The shaped samples were placed in greased glass baking pans and again placed into the incubator for 20 min in order to maintain the proofing step, which is defined as the last fermentation. Then, the samples were ready for baking.

2.3 Experimental Design

Response surface methodology (RSM) was used to relate baking responses to baking conditions. RSM is a statistical technique that uses quantitative data to determine and simultaneously solve multivariate equations, which specify the optimum product for a specified set of factors through mathematical models. These models consider interactions among the test factors and can be used to determine how the product changes with changes in the factor levels (Giovanni, 1983). In this study, central composite design was used. There were four independent variables, which were baking time, power of upper halogen lamps, power of lower halogen lamp, and power of microwave. For convenience actual values were converted to coded values. Table 2.1 shows factor and coded levels used in the experiment. Experimental design is shown in Table 2.2.

Table 2.1 Coded and uncoded independent variables used in RSM design

Symbol	Independent variable	Coded levels				
		-2	-1	0	+1	+2
		Factor levels				
X_1	Time (min)	4	4.5	5	5.5	6
X_2	Upper Halogen Lamp Power (%)	40	50	60	70	80
X_3	Lower Halogen Lamp Power (%)	40	50	60	70	80
X_4	Microwave Power (%)	20	30	40	50	60

Table 2.2 Experimental points of the Central Composite Design

Experiment number	Time (min)	UHL Power (%)	LHL Power (%)	MW Power (%)
1	+1	+1	+1	+1
2	-1	+1	+1	+1
3	+1	+1	+1	-1
4	+1	+1	-1	+1
5	+1	-1	+1	+1
6	-1	+1	+1	-1
7	-1	+1	-1	+1
8	-1	-1	+1	+1
9	+1	+1	-1	-1
10	+1	-1	+1	-1
11	+1	-1	-1	+1
12	-1	+1	-1	-1
13	-1	-1	+1	-1
14	-1	-1	-1	+1
15	+1	-1	-1	-1

16	-1	-1	-1	-1
17	0	+2	0	0
18	0	0	+2	0
19	0	0	0	+2
20	+2	0	0	0
21	0	-2	0	0
22	0	0	-2	0
23	0	0	0	-2
24	-2	0	0	0
25-36	0	0	0	0

Experiments were performed in random order

2.4 Microwave- Halogen Lamp Combination Oven Baking

Halogen lamp-microwave oven (Advantium oven^{TM}, General Electric Company, Louisville, KY, USA) is the combination of microwave heating and halogen lamp heating. There are two halogen lamps at the top of the oven and one halogen lamp at the bottom of the turntable. The turntable maintains uniform cooking conditions for the food sample. Figure 2.1 shows the schematic representation of the halogen lamp-microwave combination oven. Preliminary experiments showed that breads baked in combination oven lost significant amount of moisture. Therefore, two beakers, each containing 400 ml water, were placed at the corners of the oven to provide humidity during baking. The power of the combination oven when microwave was operating was calculated as 706 W by IMPI 2 L test (Buffler, 1993). One bread was baked at a time.

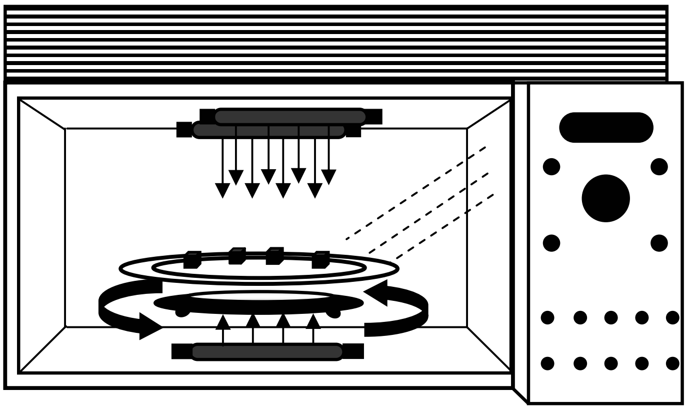


Figure 2.1 Schematic representation of the halogen lamp-microwave combination oven

2.5 Determination of Power of Microwave Oven

For the determination of the microwave oven power IMPI 2-liter test was used (Buffler, 1993). The oven was operated at the highest power (100%) with a load of 2000±5 g of water placed in two 1 L Pyrex beakers. The initial water temperature was adjusted to be 20±2 ºC. The beakers were placed in the center of the oven, side by side in the width dimensions of the cavity. The oven was turned on for 2 min and 2 s. Final temperatures of water were measured immediately after the oven was turned off. The power measurement was replicated three times. The power was calculated by using Equation 2.1.

$$\mathrm{P(W)} = \frac{mc_p\left(\Delta T_1 + \Delta T_2\right)}{2\Delta t} \tag{2.1}$$

where, ΔT_1 and ΔT_2 are the temperature rises of the water in the two beakers calculated by subtracting the initial water temperature from the final temperature, m is the total mass of water (kg), c_p is the specific heat of water (J/kg°C), and Δt is time (s).

2.6 Conventional baking

For the conventional baking, breads having the same formulation were baked in a commercial electrical oven (Arçelik ARMF 4 Plus, Turkey). The prepared dough samples were baked at 200ºC for 13 min, which was determined as the optimum baking condition by Keskin et al. (2004a). The oven was preheated at 200ºC for 2 min before the baking process. Four breads were baked at a time.

2.7 Quality Measurements

After baking the breads, in order to determine the optimum baking point, the quality measurements were performed. The quality parameters were the weight loss, color, specific volume, texture profile, and porosity of the breads.

2.7.1 Weight Loss

The weight loss of the breads was calculated by measuring the weight of the dough before and bread after the baking process. The following equation was used to express the weight loss:

$$\text{Weight loss (\%)} = \frac{W_i - W_f}{W_i} \times 100 \qquad (2.2)$$

where,

W_i : weight of the dough before baking,

W_f : weight of the bread just after baking.

2.7.2 Color

The crust color of the samples were measured by using Minolta color reader (CR-10, Japan) and expressed as Hunter L*, a*, b* color values. Three data were taken from crust of each sample and total color change (ΔE) was calculated from equation (2.3).

$$\Delta E = [\ (L^* - L_0\ )^2 + (a^* - a_0)^2 + (b^* - b_0)^2\ ]^{1/2} \tag{2.3}$$

Dough was selected as the reference point and its L*, a*, and b* values were represented as L_0, a_0, b_0. L*, a*, and b* values represent the lightness changing from 0 (black) to 100 (white), redness (+60) to greenness (-60), yellowness (+60) to blueness (-60) of the dough respectively.

2.7.3 Specific Volume

Specific volume of the breads were determined by the rape seed displacement method (AACC, 1988). In order to find the specific volume of the bread, first, the bread was weighed and then placed into a container, which had a known volume. Then, the rape seeds were added and the tapping process began. After tapping, the container filled with the bread and rape seeds was re-weighed. If different value was read, more rape seeds were added and the surface was smoothed by the help of a ruler. The same procedure continued until constant weight was measured. The bulk density of the rape seeds were measured by the same procedure and calculated as 0.667 g/cm^3. The volume of the breads was calculated from the following equations:

$$W_{seeds} = W_{total} - W_{bread} - W_{container} \tag{2.4}$$

$$V_{seeds} = W_{seeds} / \rho_{seeds} \tag{2.5}$$

$$V_{bread} = V_{container} - V_{seeds} \tag{2.6}$$

where, W represents ‘weight (g)’, V is ‘volume (cm^3)’, and ρ is ‘density (g/cm^3)’.

The specific volume was calculated by dividing the volume of the bread by its weight;

$$SV_{bread} = V_{bread} / W_{bread} \tag{2.7}$$

where SV is the specific volume (cm^3/g).

2.7.4 Texture Profile

Firmness, chewiness, and springiness of the breads were measured as the textural properties by using a texture analyzer (TAPlus, Lloyd Instruments, UK). Bread samples were compressed for 25% at a speed of 55 mm/min. A load of 50 N was used and the samples were prepared according to the method of AACC (1988) that had a thickness of 1.5 cm. The diameter of the probe was 2.5 cm. Firmness value is the maximum force required to compress the food material to its 25% of its thickness. Springiness is defined as the elasticity of the material that can be stretched and returns to its original length and chewiness can only be applied for solids and calculated as gumminess*springiness. Two of the texture profiles were given as examples in Appendix A.

2.7.5 Porosity

Porosity was measured by using the method of Zanoni et al. (1995). Porosity can be defined as the ratio of the volume of the pores to the total volume of the product:

$$\varepsilon = (V_t - V_{np}) / V_t \qquad (2.8)$$

where,

V_t = total volume of the sample,

V_{np} = volume of the non-porous material in the sample.

An apparatus having a constant basement area was designed, which allowed pores to be removed from the bread samples, to measure porosity. The prepared samples were put inside this apparatus and constant force was applied for 1 min. Since the basement area was constant, porosity can be defined as:

$$\varepsilon = (H_0 - H_f) / H_0 \qquad (2.9)$$

where,

H_0 = initial height of the sample (mm),

H_f = final height of the sample (mm) after compression.

2.8 Statistical Analysis

Multiple regression analysis was performed to fit second-order models or third-order models to dependent variables, by using Minitab Release 13.1 Software. The models were used to plot contour surfaces, three-dimensional plots, and to determine the optimum baking conditions. Contour surfaces and 3-D plots were plotted by Surfer Version 6.01, surface mapping system. In order to find the optimum baking conditions, Matlab Version 6.5 software was used. The program was written to find the optimum point by considering a maximum specific volume, a minimum texture and weight loss and constraint of color. Color constraint was obtained by using ΔE values of conventionally baked breads. Analysis of variance (ANOVA) was performed in order to determine the significant differences between the independent variables ($p \leq 0.05$). If significant differences were observed, variable means were compared by Duncan's multiple comparison range test. Four replications were used in all of the measurements.

2.9 Neural Network

In this study, three layered feed forward artificial neural network structures were constructed. The input layer was consisted of four neurons for each neural network, which corresponded to baking time, upper halogen lamp power, lower halogen lamp power, and microwave power. The output layer had one neuron that represented weight loss, ΔE value, specific volume, or firmness of the bread samples. Therefore, four different network structures were developed for each of the parameters by using the neural network toolbox of Matlab Version 6.5 software. A simple input-1hidden-output system structure with 2 nodes was chosen. A hyperbolic-tangent sigmoid transfer function and linear transfer function were used. The back-propagation feed forward algorithm was utilized in model training. This type of network has been selected because it is known as a good pattern classifier (Torrecilla et al., 2004). The feed forward algorithm uses the supervised training technique where the network weights and biases are initialized randomly at the beginning of the training phase. For a given set of inputs to the network, the response to each neuron in the output layer was calculated and compared with the corresponding desired output response. To avoid the potential problem of over-training or memorization, the option of saving the best configuration was selected where the network with the best result was saved during the selected long number of training cycles of 100. The response values found by the models constructed by the neural network were compared with the experimental data.

CHAPTER 3

RESULTS AND DISCUSSION

In the first part of the study, response surface methodology was used for the optimization process, and in the second part, as an alternative way to RSM, artificial neural networks were constructed.

3.1 Response Surface Methodology

In this study second-order polynomial models were developed as a function of independent variables to express the responses by using the Minitab Program.

$$Y = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + b_{11}X_1^2 + b_{22}X_2^2 + b_{33}X_3^2 + b_{44}X_4^2 + b_{12}X_{12} + b_{13}X_{13} + b_{14}X_{14} + b_{23}X_{23} + b_{24}X_{24} + b_{34}X_{34}$$

In this equation Y represents the dependent variable (weight loss, ΔE value, specific volume, firmness, chewiness, springiness or porosity), X_i' s are the independent variables (baking time, power of upper halogen lamps, power of lower halogen lamp, power of microwave) and b_i's are the model constants.

The regression equations and coefficients were determined from multiple regression analysis of the experimental data. The experimental data are given in Tables B1-B2. The model equations and the regression coefficients are given in Table 3.1. The coefficient of determination (r^2), which shows the measure of fitting the data, was very high especially for weight loss and color. Regression tables are given in Tables C1-C7.

Table 3.1 Model equations for bread baked by different time and power combinations

Quality Parameter	**Equation**	r^2
Weight loss	$Y_1=9.69+1.50X_1^{***}+0.753X_2^{***}+0.313X_3+2.94X_4^{***}+0.045X_1^2+0.098X_2^2+0.265X_3^2-0.072X_4^2-0.110X_1X_2+0.191X_1X_3+0.562X_1X_4^{**}+0.176X_2X_3-0.173X_2X_4-0.050X_3X_4$	0.957
ΔE value	$Y_2=29.1+2.74X_1^{***}+8.89X_2^{***}+0.553X_3+0.930X_4^{*}-0.871X_1^{2*}+0.119X_2^2+0.504X_3^2-0.242X_4^2-0.323X_1X_2+0.895X_1X_3+0.282X_1X_4-0.249X_2X_3+0.337X_2X_4-0.016X_3X_4$	0.961
Specific volume	$Y_3=1.83+0.0333X_1^{*}+0.0292X_2^{*}+0.0111X_3+0.105X_4^{***}+0.0091X_1^2+0.0067X_2^2-0.0120X_3^2-0.0038X_4^2-0.0489X_1X_2^{**}-0.0147X_1X_3+0.0256X_1X_4-0.0347X_2X_3-0.0545X_2X_4^{**}-0.0312X_3X_4$	0.825
Firmness	$Y_4=0.986+0.0650X_1^{*}-0.0199X_2-0.0036X_3+0.203X_4^{***}-0.0197X_1^2+0.0119X_2^2+0.0700X_3^{2**}+0.0682X_4^{2**}+0.0324X_1X_2+0.0608X_1X_3-0.0246X_1X_4+0.0009X_2X_3-0.0064X_2X_4-0.0335X_3X_4$	0.797
Chewiness	$Y_5=0.160+0.0124X_1^{**}-0.00345X_2-0.00021X_3+0.0372X_4^{***}-0.00141X_1^2+0.00154X_2^2+0.0119X_3^{2**}+0.0132X_4^{2**}+0.00498X_1X_2+0.0109X_1X_3-0.00363X_1X_4-0.00082X_2X_3-0.00000X_2X_4-0.00546X_3X_4$	0.837
Porosity	$Y_6=68.2-0.289X_1+1.14X_2^{*}+0.254X_3+1.36X_4^{*}+0.342X_1^2-0.378X_2^2-0.224X_3^2-0.176X_4^2+0.124X_1X_2-0.388X_1X_3-0.308X_1X_4-0.110X_2X_3-0.759X_2X_4^{*}-0.247X_3X_4+0.365X_1^3-0.181X_2^3-0.001X_3^3+0.157X_1X_2X_3+0.119X_1X_2X_4-0.350X_2X_3X_4-1.79X_4X_1^{2**}$	0.751
Springiness	$Y_7=3.01+0.0087X_1+0.0396X_2^{**}-0.0055X_3+0.0352X_4^{*}+0.0189X_1^{2*}-0.0320X_2^{2***}+0.0132X_3^2+0.0104X_4^2+0.00210X_1X_2+0.00105X_1X_3+0.00741X_1X_4+0.00703X_2X_3-0.0175X_2X_4-0.00464X_3X_4+0.00275X_1^3-0.0330X_2^{3***}+0.00240X_3^3-0.00411X_1X_2X_3+0.00607X_1X_2X_4+0.00583X_2X_3X_4-0.0273X_4X_1^2$	0.880

* Means term is significant at $p \le 0.05$, ** Means term is significant at $p \le 0.01$,

*** Means term is significant at $p \le 0.001$

3.1.1 Weight Loss

Baking time, power of upper halogen lamp, and microwave were found to be the most significant variables (p=0.000 for all of the three) on affecting the weight loss of breads in halogen lamp-microwave combination oven (Table 3.1). As baking time and power of the microwave increased, weight loss increased (Fig. 3.1). Microwave power is an important parameter showing that microwaves are sent into the oven cavity at the given percentage of whole processing time. As microwave power increased, more interior pressure occurred which increased liquid flow through the food boundary (Datta, 1990). As a result, higher weight loss was observed. Higher weight loss in the presence of high microwave power levels was also observed by other researchers (Sumnu et al., 1999 and Keskin et al., 2004a).

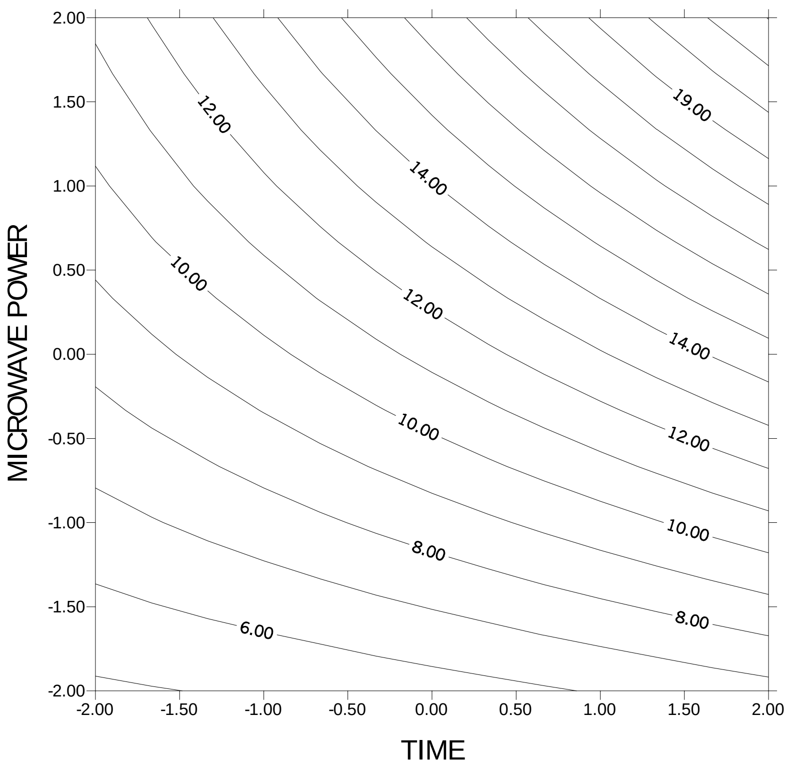


Figure 3.1 Effect of microwave power (X_4) and time (X_1) on weight loss (%) of breads ($X_2 = X_3 = 1$)

As the upper halogen lamp power increased, the heat radiated to the bread increased, so more energy was penetrated and higher weight loss was observed (Fig. 3.2). Surfaces of the products baked in microwave oven were reported to be soggy (Datta, 2001). It was observed that the use of upper halogen lamp prevented the sogginess problem.

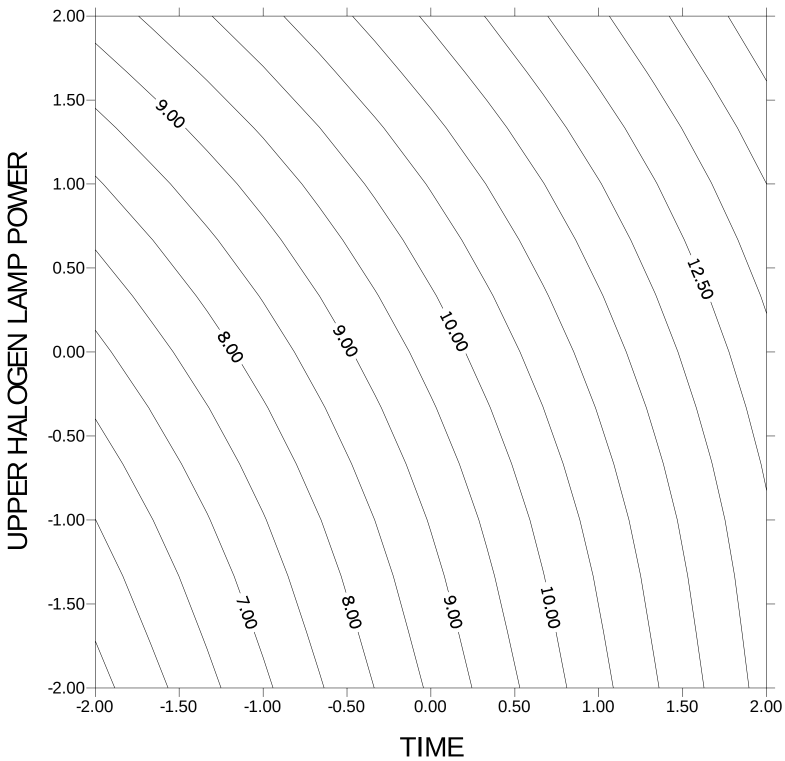
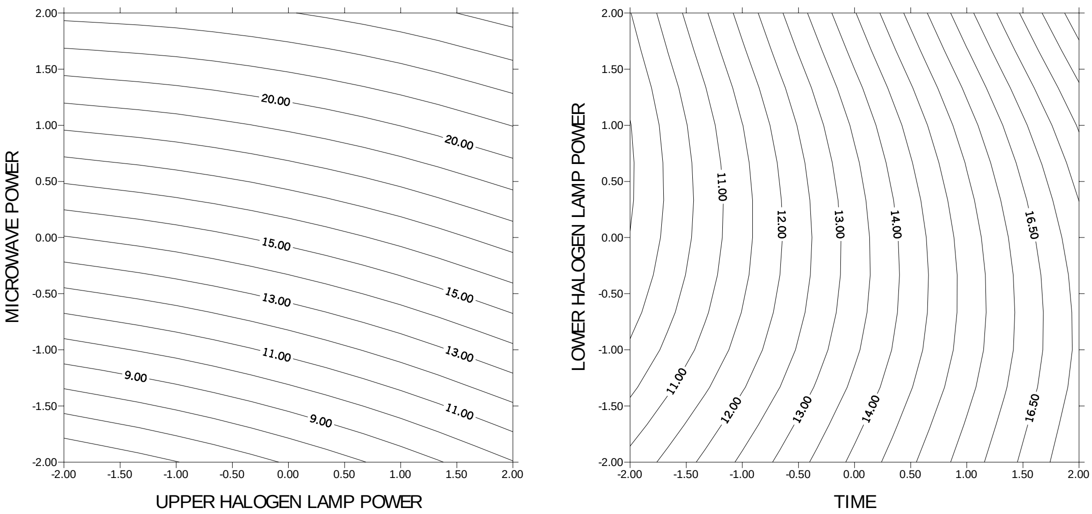


Figure 3.2 Effect of upper halogen lamp power (X_2) and time (X_1) on weight loss (%) of breads ($X_3 = X_4 = 0$)

When the effects of microwave power and upper halogen lamp power were compared, microwave power was found to be more effective on weight loss (Fig. 3.3a). This situation was also observed by Keskin, et al. (2004a). Lower halogen lamp power did not have a significant effect on the weight loss of breads (Table 3.1) (Fig. 3.3b). Since the lower halogen lamp is placed under the turntable, its effect on weight loss becomes insignificant.



a b

Figure 3.3 a. Effect of microwave power (X_4) and upper halogen power (X_2) on weight loss (%) of breads ($X_1 = X_3 = 2$) **b.** Effect of lower halogen lamp power (X_3) and time (X_1) on weight loss (%) of breads ($X_3 = X_4 = 1$)

3.1.2 Color

Upper halogen lamp power and baking time were found to be the most significant parameters on affecting the ΔE value of the breads (Table 3.1). The increase in upper halogen lamp power and baking time increased the ΔE value, which is an index of color change significantly (Fig. 3.4). As baking time and upper halogen lamp power increased, the air temperature inside the oven increased, resulting higher surface temperatures of bread required for the Maillard browning reactions. Maillard reaction is a type of non-enzymatic browning which involves the reaction of simple sugars (carbonyl groups) and amino acids (free amino groups). Higher concentration of reducing sugars will result in increased levels of Maillard reaction products, which are responsible for the darkening of the crust. In addition, electromagnetic radiation is focused near the surface due to its low penetration depth resulting in higher surface temperatures. Color change of breads was also reported to be affected by halogen lamp power and baking time by other researchers (Keskin et al., 2004a). The increase in time at higher upper halogen lamp powers found to be insignificant for the color change of the breads. This was also supported by Duncan's multiple comparison test (Table D.2) which showed that there was no significant difference between the coded values of 0, 1, and 2 of time. The ΔE values for the conventionally baked breads were 35.9. The color of the breads that were baked at higher halogen lamp powers had similar ΔE values compared with the ones baked in conventional oven. As mentioned before, this result could be explained by the higher oven temperature during baking in the presence of high halogen lamp powers, which provided the browning reactions to occur.

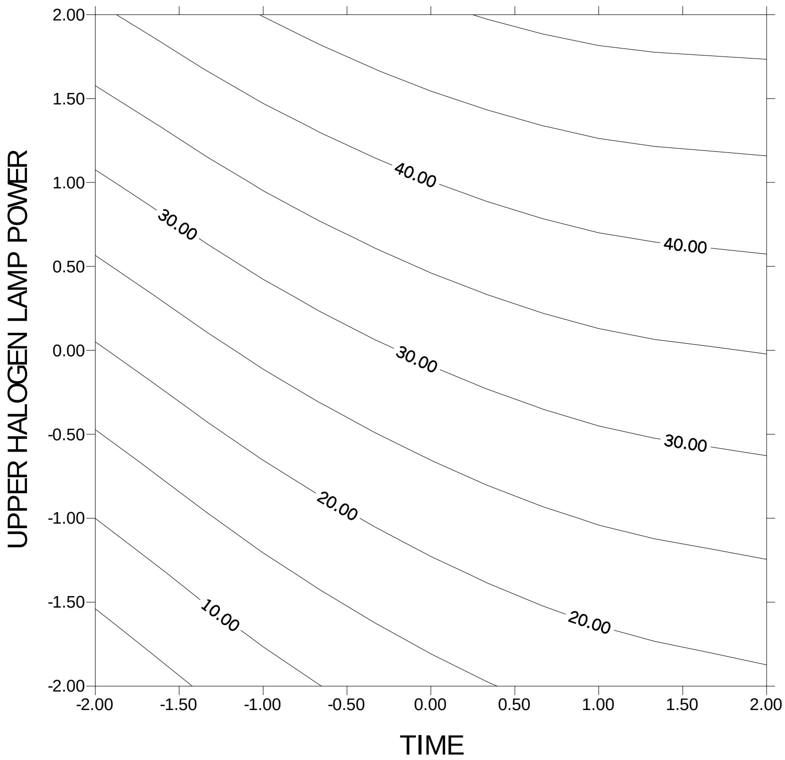


Figure 3.4 Effect of upper halogen lamp power (X_2) and time (X_1) on ΔE value of breads ($X_3 = X_4 = 1$)

The increase in microwave power did not affect ΔE value for lower baking times (Fig. 3.5). However, when baking time was long, the increase in microwave power increased the ΔE value. This might be explained by drying of the product.

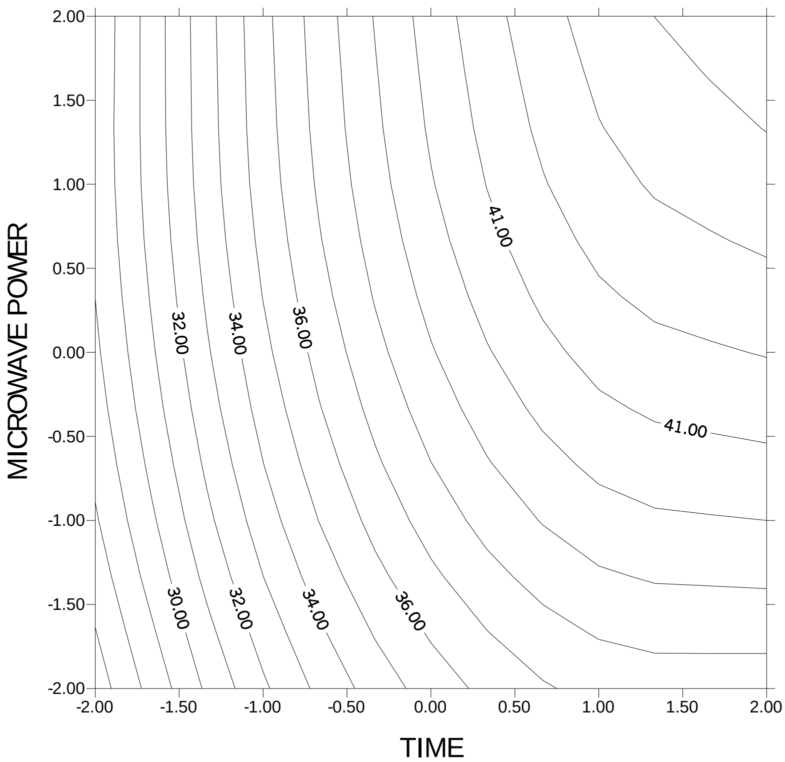


Figure 3.5 Effect of microwave power (X_4) and time (X_1) on ΔE value of breads ($X_2 = X_3 = 1$)

Lower halogen lamp power was not found to be significantly effective on the color of the breads (p=0.202) (Table 3.1) (Table D.2). When the significance of upper halogen lamp power and lower halogen lamp power were compared it was observed that lower halogen lamp power had almost no effect on the ΔE value of the breads (Fig. 3.6).

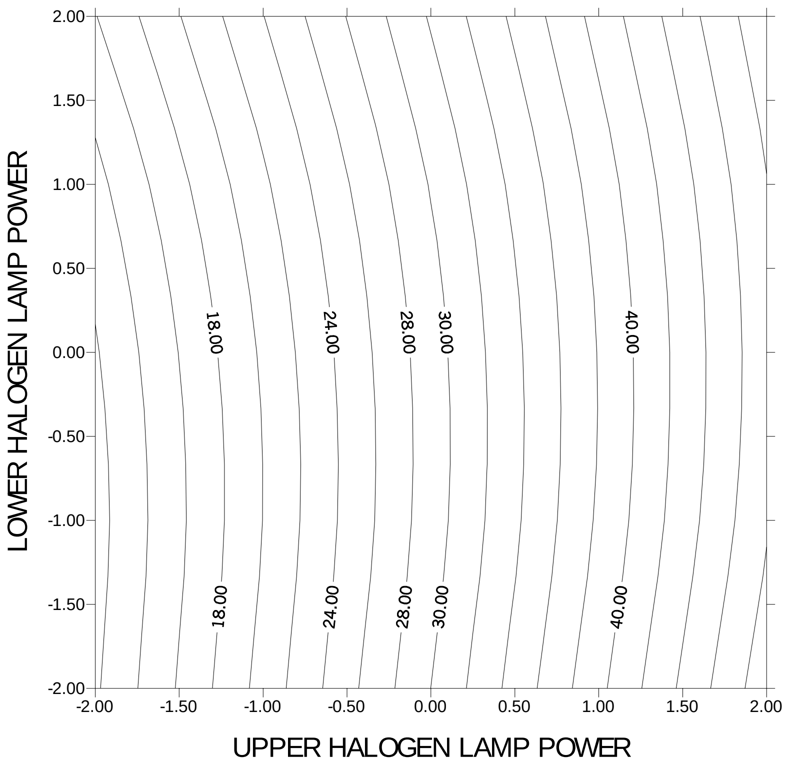


Figure 3.6 Effect of lower halogen lamp power (X_3) and upper halogen lamp power (X_2) on ΔE value of breads ($X_1 = X_4 = 0$)

3.1.3 Specific Volume

Time, power of upper halogen lamps, and power of microwave were found to be significant factors on affecting the specific volume of the breads (Table 3.1). As baking time and microwave power increased, specific volume of breads increased (Fig. 3.7). Specific volume was more influenced by increase in microwave power as compared to time. The increase in microwave power may increase internal pressure of breads, which may result in higher specific volume. The increase in specific volume when microwave power was increased was reported by other researchers too (Keskin et al., 2004a and Şumnu et al., 2000).

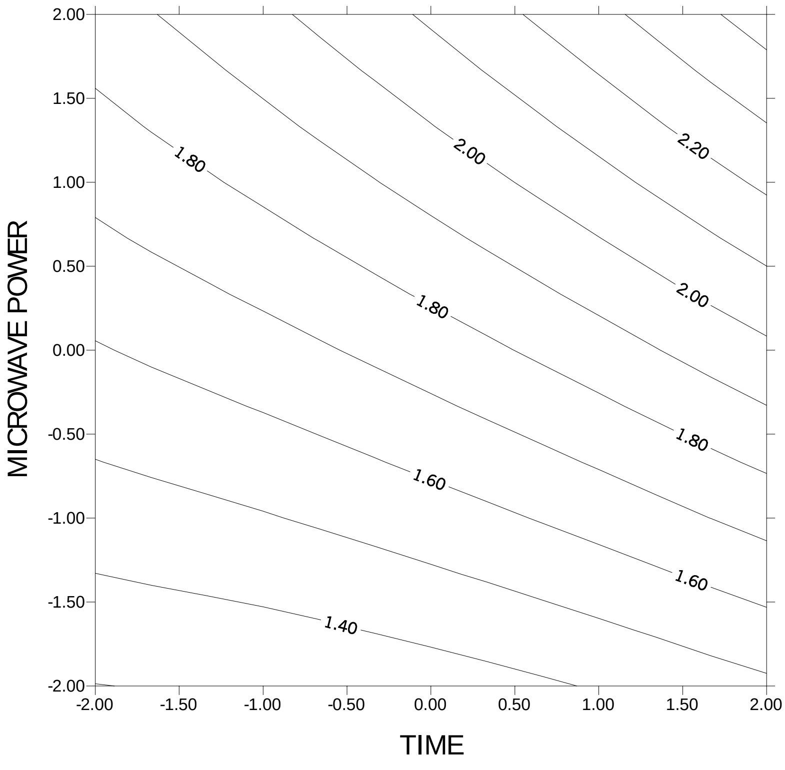


Figure 3.7 Effect of microwave power (X_4) and time (X_1) on specific volume (cm^3/g) of breads ($X_2 = X_3 = -1$)

When the upper halogen lamp power was increased, the specific volume of breads decreased (Fig. 3.8). This may be due to the sudden crust formation, which prevented the transfer of heat to the inner parts, necessary for the formation of the starch-gluten matrix. This matrix provides optimum dough development and gas retention which results in higher specific volume.

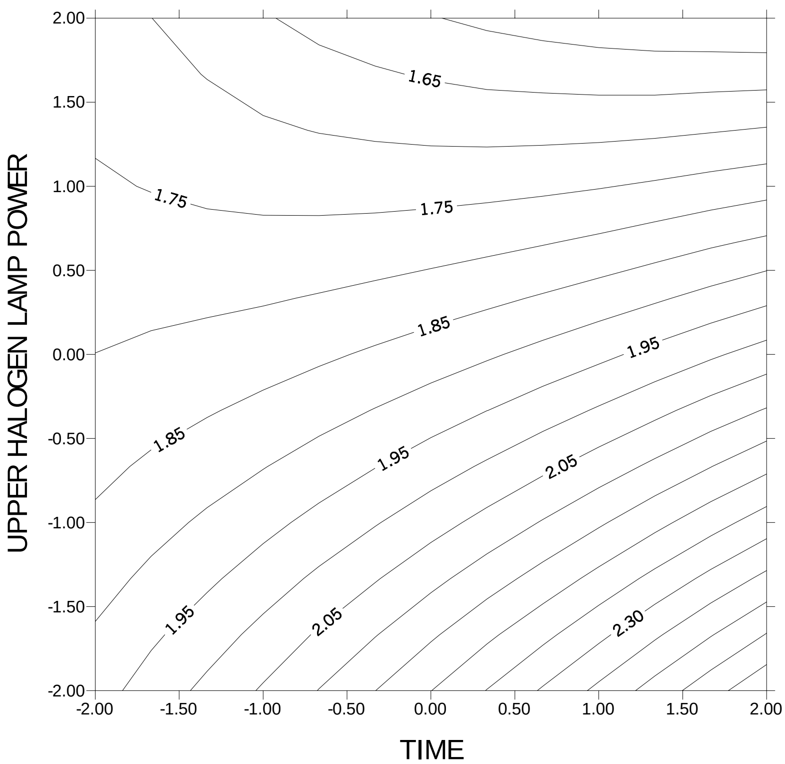


Figure 3.8 Effect of upper halogen lamp power (X_2) and time (X_1) on specific volume (cm^3/g) of breads ($X_3 = X_4 = 2$)

The interaction of microwave power with upper halogen lamp power in affecting the specific volume of the breads was found to be significant (Table 3.1). The effects of microwave power and upper halogen lamp power can be seen together in Figure 3.9. It was observed that for lower values of upper halogen lamp power, microwave power was significant but as the upper halogen lamp power increased, the significance of microwave power decreased.

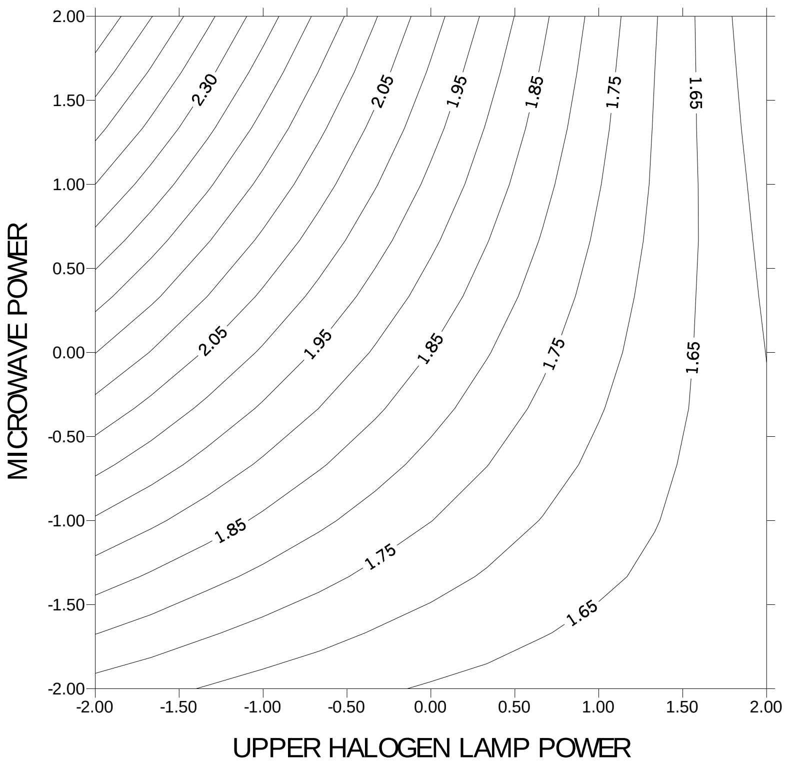


Figure 3.9 Effect of microwave power (X_4) and upper halogen lamp power (X_2) on specific volume (cm^3/g) of breads ($X_1 = X_3 = 2$)

The lower halogen lamp power was found to be insignificant on specific volume of breads (Table 3.1). Figure 3.10 shows the effect of lower halogen lamp power and time on specific volume of breads. It seems that an optimum value for specific volume could be obtained for higher time values. However, when baking time was higher than 6 min (as coded +2), the bread samples burned.

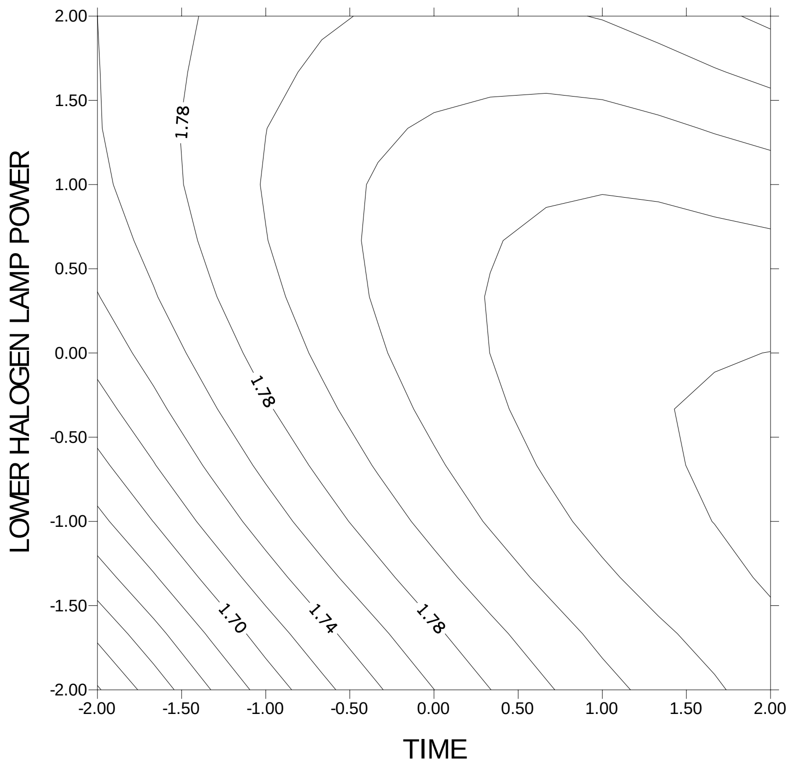


Figure 3.10 Effect of lower halogen lamp power (X_3) and time (X_1) on specific volume (cm^3/g) of breads ($X_2 = X_4 = 0$)

3.1.4 Firmness

Firmness was found to be affected by microwave power and time significantly. The increase in microwave power and baking time increased the firmness of the breads (Fig. 3.11). The reason for high firmness values as microwave power increased may be due to high moisture loss, interactions of microwave with gluten and high amylose leaching during baking (Shukla, 1993; Keskin, 2003). The firmness value for the conventionally baked breads were found as 0.71 N. At lower baking time and microwave power combinations, firmness values similar to conventionally baked breads were observed. For lower values of time and microwave power, the effect of microwave power was insignificant but as microwave power increased, its significance also increased (Fig. 3.11). The increase in firmness of breads with respect to time may be explained by the increase in weight loss during the baking process.

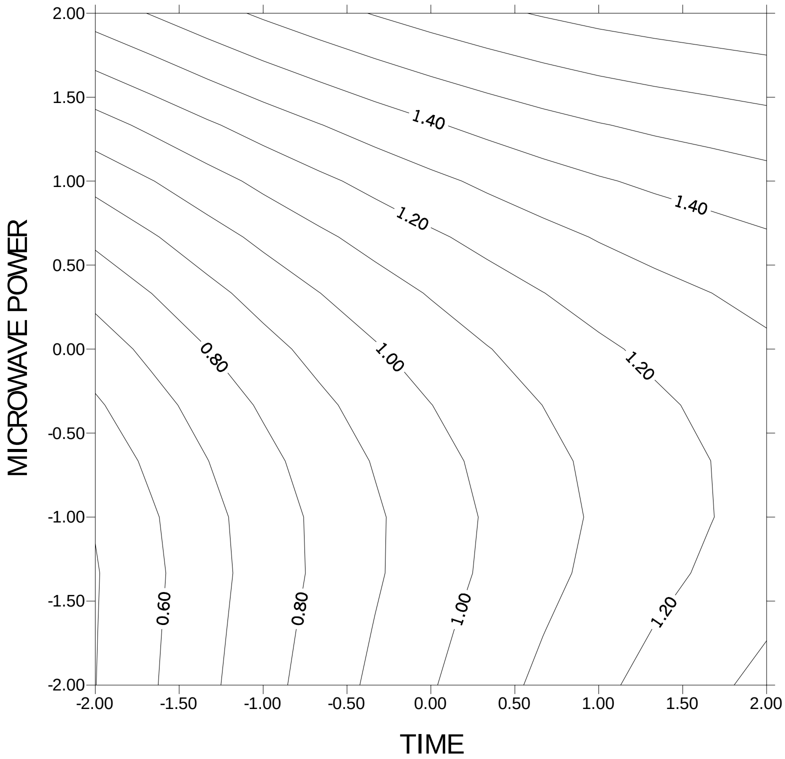


Figure 3. 11 Effect of microwave power (X_4) and time (X_1) on firmness (N) of breads ($X_2 = X_3 = 1$)

For constant baking time (X_1 = 1) and lower halogen lamp power (X_3 = 1), an optimum firmness value was observed at lower levels of microwave and upper halogen lamp powers (Fig. 3.12).

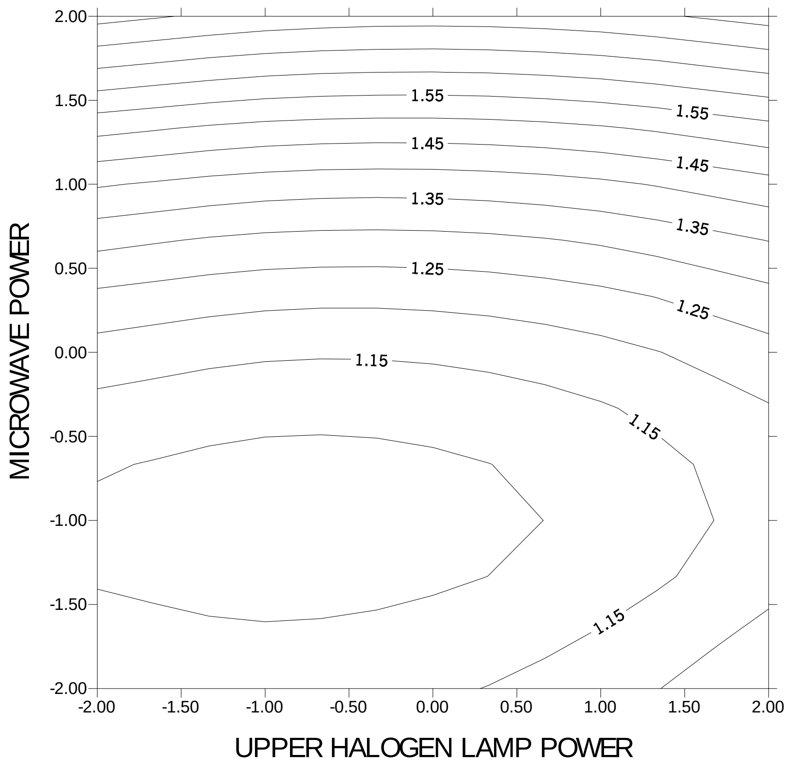


Figure 3.12 Effect of microwave power (X_4) and upper halogen lamp power (X_2) on firmness (N) of breads ($X_1 = X_3 = 1$)

The effect of upper halogen lamp power on firmness was found to be insignificant (Table 3.1). This was also supported by Duncan's multiple comparison test which showed that there were no significant differences between the coded values of -2, -1, 0, 1, and 2 for the upper halogen lamp power (Table D.4).

Lower halogen lamp power was also found to be insignificant ($p \geq 0.05$) on firmness values of the breads. Figure 3.13 shows the effect of lower halogen lamp and microwave power on firmness. For lower values of microwave power, an optimum firmness value was observed but as the power of microwave increased, the insignificance of lower halogen lamp power on firmness can be seen.

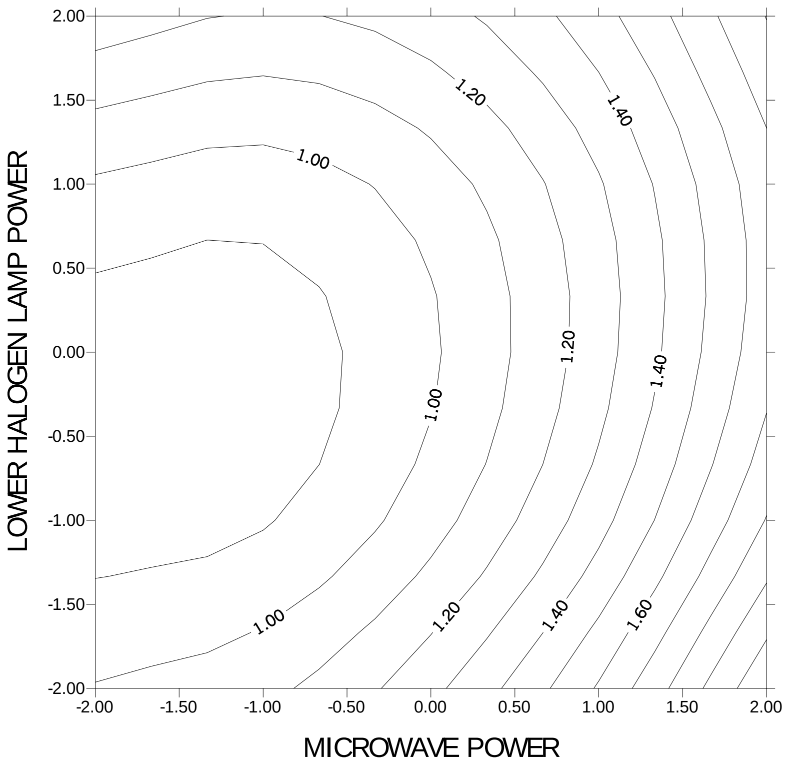


Figure 3.13 Effect of microwave power (X_4) and lower halogen lamp power (X_3) on firmness (N) of breads ($X_1 = X_2 = 0$)

Data of porosity, springiness, and chewiness of the breads were also modeled. For chewiness, a second-order model was fitted and a high coefficient of determination was observed ($r^2 = 0.837$) (Table 3.1). Baking time and microwave power were found to be significant for chewiness as it was observed for firmness (Table 3.1). For porosity and springiness, third-order models were developed (r^2 = 0.751 & r^2 = 0.880 respectively) since data did not fit second order model. Some of the terms were missing in the model equations of the porosity and springiness, since the Minitab program removed these terms as they were highly correlated with other X variables. Upper halogen lamp power and microwave power were found to be significant on affecting both porosity and springiness (Table 3.1).

3.1.5 Determination of the Optimum Point

In order to find the optimum point, a Matlab program was written by considering a maximum specific volume, a minimum firmness and weight loss and a constraint of ΔE value. The constraint was determined by using the ΔE values of the conventionally baked breads, which was 35.9. The written Matlab program is shown in Appendix E.

The optimum point calculated by the help of the Matlab program is given in Table 3.2. The optimum point found was rounded since the oven could not operate at the midpoints and the corresponding uncoded and rounded values are also given Table 3.2. Table 3.3 gives the responses calculated from the model equations by using the optimum point. In order to make a comparison, the responses measured for the conventionally baked breads are also given in Table 3.3.

Table 3.2 The calculated and uncoded optimum point

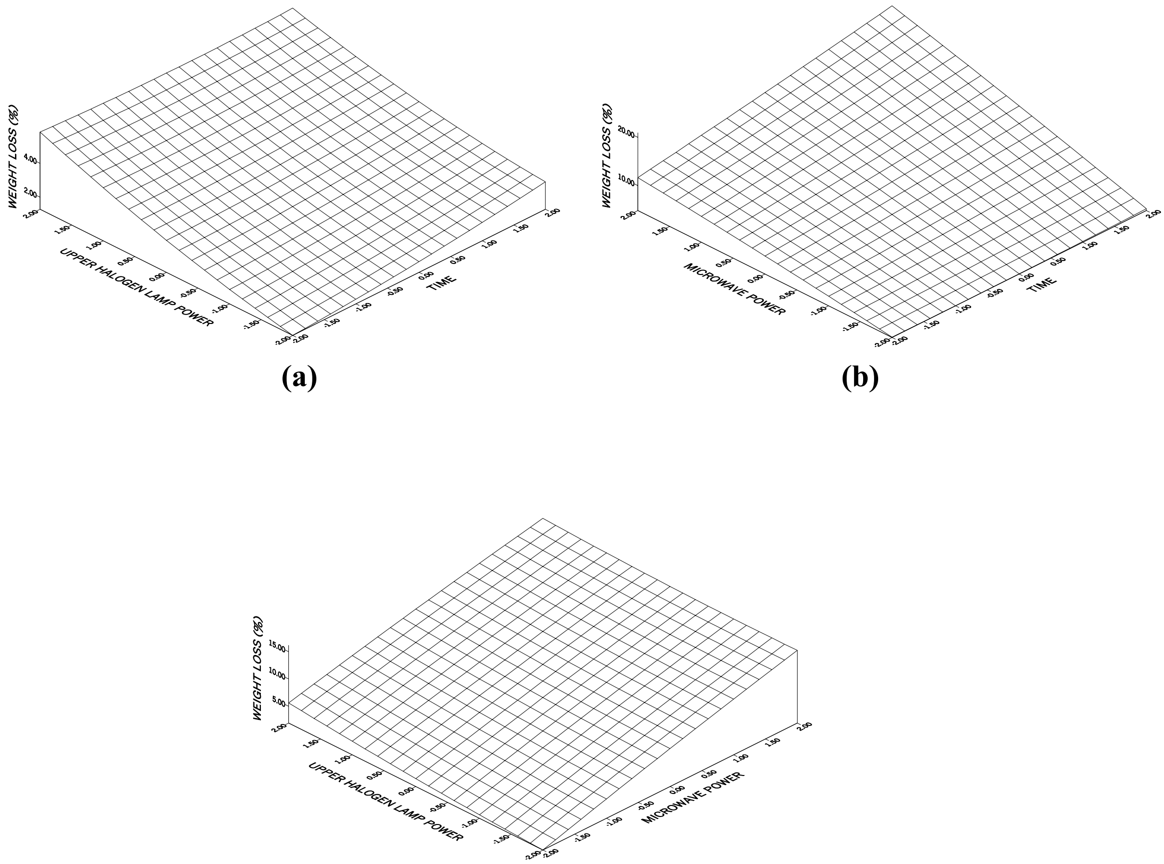
Factors	Optimum coded value	Optimum uncoded value
Time (X_1)	0.1574	5 min
UHLP (X_2)	1.0888	70 %
LHLP (X_3)	–1.3177	50 %
MWP (X_4)	–2.0000	20 %

Table 3.3 Comparison of responses for conventionally baked breads and responses calculated for the optimum point for halogen lamp-microwave combination baked bread

Responses	Conventional baking	Halogen lamp-microwave combination baking
Weight loss (%)	4.06	4.39
ΔE value	35.7	34.8
Specific volume (cm^3/g)	1.63	1.70
Firmness (N)	0.71	0.86
Porosity	64.1	65.3
Chewiness (Nmm)	1.05	1.38
Springiness (mm)	2.92	3.00

As can be seen from Table 3.3, breads baked in halogen lamp-microwave combination oven at the optimum condition of 5 min of baking at 70% upper halogen lamp power, 50% lower halogen lamp power, and 20% microwave power were comparable in quality in terms of textural characteristic, specific volume, porosity, and color with conventional baked ones. Firmness and chewiness values of these breads were found to be slightly higher than that of the conventionally baked ones. This may be due to the higher moisture loss obtained in combination oven. In this study, lower and acceptable firmness and weight loss values were obtained for breads baked in halogen lamp-microwave combination oven as compared to the study performed by Keskin et al. (2004a) since water was also used in the oven during baking to provide humidity. In the halogen lamp-microwave combination oven, it was possible to achieve ΔE value of crust very close to the conventional oven. In addition, when halogen lamp-microwave combination oven was used, conventional baking time was reduced by about 60%.

The responses for the calculated optimum point were shown in 3-D plots. Figure 3.14(a) and Figure 3.14(b) show the effect of microwave power and upper halogen lamp power with respect to time on weight loss of breads, respectively. As can be seen from the Figure 3.14(a), the increase in microwave power, increased the weight loss significantly at the optimum point of 70% and 50% for upper and lower halogen lamp powers respectively. As the power of the upper halogen lamps increased, there was significant increase in weight loss (Fig. 3.14(b)). Figure 3.14(c) shows response surface for the effect of upper halogen lamp and microwave power on weight loss of breads at the optimum conditions of 5 min baking time and 50% lower halogen lamp power. The effect of microwave power was more significant on increasing weight loss as compared to upper halogen lamp power. Keskin et al. (2004a) also showed that in halogen lamp-microwave combination baking, the microwave power was more effective on weight loss than halogen lamp power.

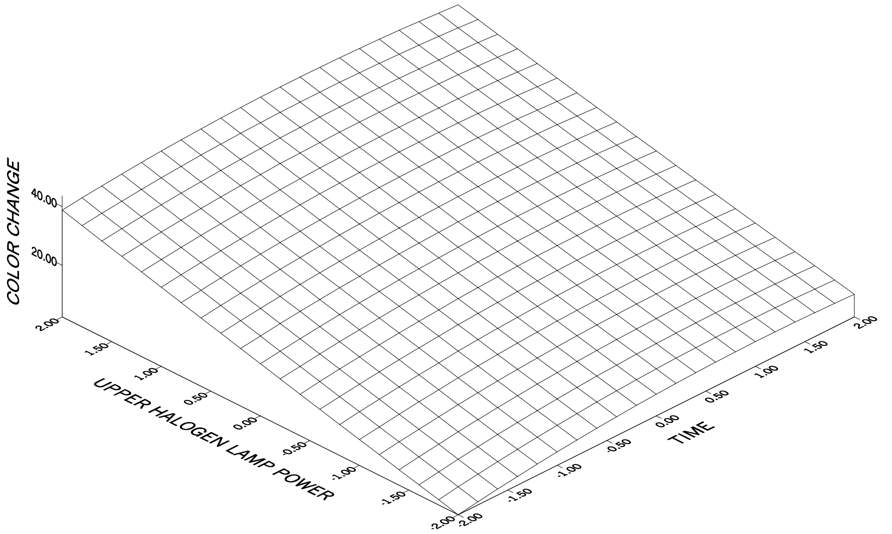


(a) **(b)**

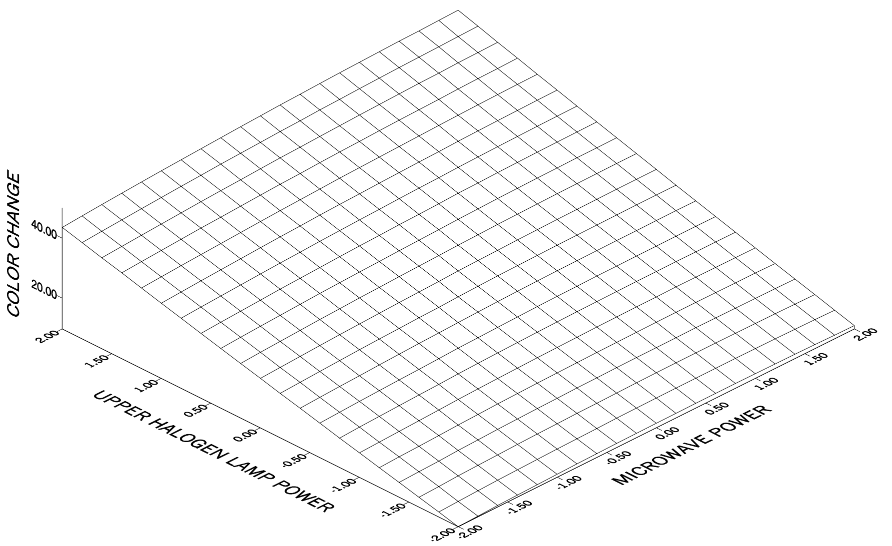
(c)

Figure 3.14 Response surfaces for weight loss of breads showing **(a)** the effects of microwave power and time (X_2 = 1, X_3 = -1) **(b)** the effects of upper halogen lamp power and time (X_3 = -1, X_4 = -2) **(c)** the effects of upper halogen lamp and microwave power (X_1 = 0, X_3 = -1)

The color change (ΔE value) of the breads was found to be affected by upper halogen lamp power and time significantly. Figure 3.15(a) shows the effect of baking time and upper halogen lamp power (at 20% and 50% microwave and lower halogen lamp power respectively) on color change in 3-D configuration. As can be seen from the figure, increase in upper halogen lamp power and baking time, increased the ΔE values. For higher values of baking time and upper halogen lamp power, ΔE values similar to conventionally baked breads were observed. As can be seen from Figure 3.15(b), the effect of microwave power on color development of the breads was insignificant.



(a)



(**b**)

Figure 3.15 Response surfaces for ΔE value of breads showing **(a)** the effects of upper halogen lamp power and time (X_3 = -1, X_4 = -2) **(b)** the effects of upper halogen lamp and microwave power (X_1 = 0, X_3 = -1)

Figure 3.16 shows the effect of microwave power and baking time for the specific volume of the breads. As can be seen from the figure, as the baking time increased, the specific volume decreased for lower values of microwave power. This may be due to the high halogen lamp power ($X_2 = 1$), which produced a thick crust that prevented the formation of the required starch-gluten matrix. When the microwave power increased, specific volume of the breads increased due to high internal pressure inside the baked breads.

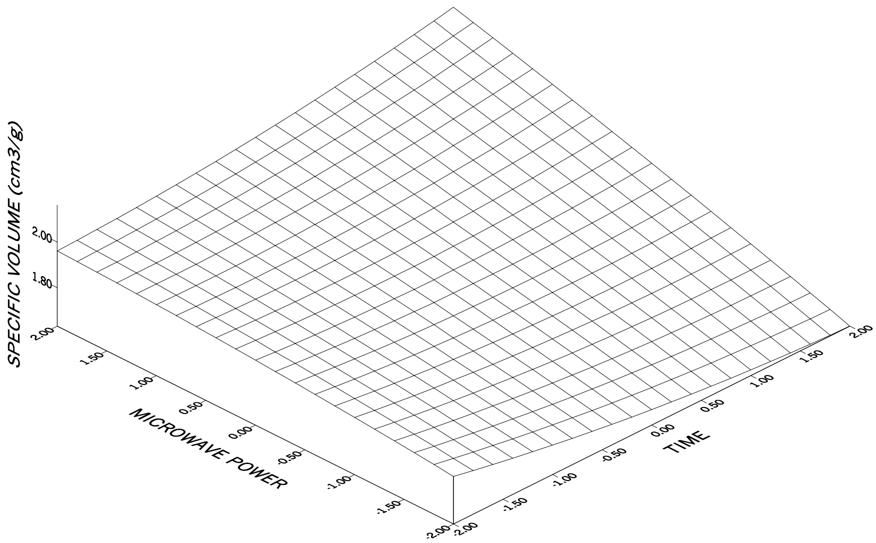
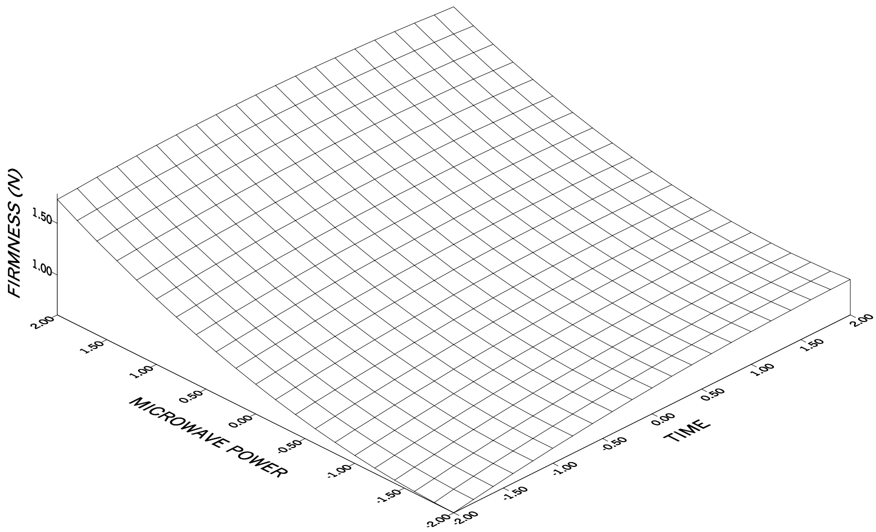
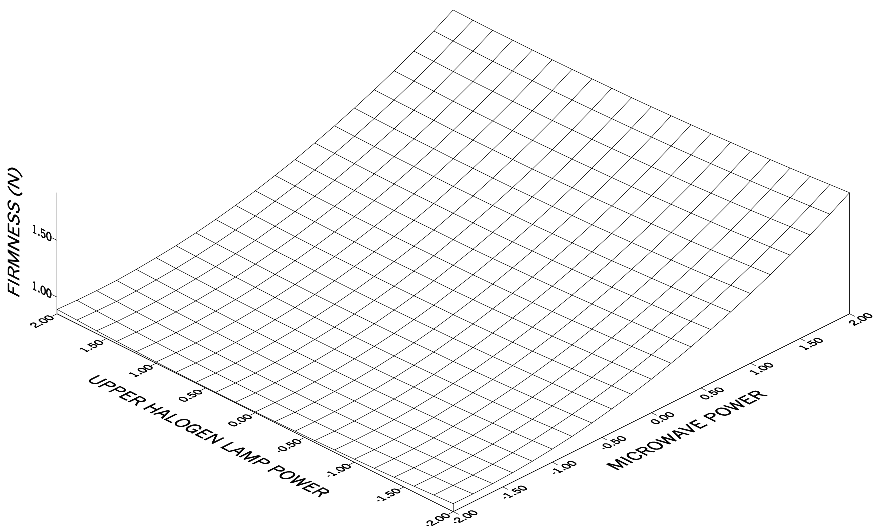


Figure 3.16 Response surface for specific volume of breads showing the effects of microwave power and time ($X_2 = 1$, $X_3 = -1$)

Microwave power and baking time were the most significant parameters affecting the firmness of the breads. Figure 3.17(a) shows that increase in microwave power increased the firmness even for the lower baking times. The increase in firmness due to high microwave power may be explained by the interactions of microwave with the gluten matrix and the increase in weight loss, which resulted in a drier product. As can be seen from Figure 3.17(b), the upper halogen lamp power was found to be insignificant even for its higher values, but the increase in microwave power increased the firmness very significantly.



(a)



(b)

Figure 3.17 Response surfaces for firmness of breads showing **(a)** the effects of microwave power and time (X_2 = 1, X_3 = -1) **(b)** the effects of upper halogen lamp and microwave power (X_1 = 0, X_3 = -1)

3.2 Artificial Neural Network

Artificial neural network was used as an alternative method to RSM to model the quality parameters of breads baked in halogen lamp-microwave combination oven. For this purpose, first, three-layer networks were constructed. The input layer consisted of four neurons for each neural network, which corresponded to baking time, upper halogen lamp power, lower halogen lamp power, and microwave power. The output layer had one neuron that represented weight loss, ΔE value, specific volume, or firmness of the bread samples. Therefore, four different network structures were developed for each of the quality parameters. The number of hidden layers was chosen to be one. It has been shown that one hidden layer is sufficient to approximate any continuous non-linear function, although more complex networks may be employed in special applications (Xie and Xiong, 1999). In addition, as the number of data was quite sparse, in order to overcome the overfitting property of neural network, a simple input-1hidden-output system structure was chosen. Several number of nodes for the hidden layer were examined and it was observed that more than two nodes created the overfitting problem. Therefore, the structure was fixed to 1 hidden layer and 2 neurons. In modeling, hyperbolic-tangent sigmoid transfer function and linear transfer function were used. The back-propagation feed forward algorithm was utilized in model training. In order to understand the network better, the parameters in equation 1.3 is given below:

$$y_v = \tilde{g}[\sum_{k=1}^{u} w_{2uv} g(\sum_{j=1}^{p} w_{1ju} x_j + b_{1j}) + b_{2u}] \tag{1.3}$$

$\tilde{g}$ was chosen to be the linear transfer function, g was the hyperbolic-tangent sigmoid transfer function, u was 2, which is the number of nodes, and p was 4, which is the number of independent variables. The notations w and b's are the weight and bias functions calculated by the program respectively. The written program and the weight and bias functions are given in Appendix F.

For the neural network study, the same experimental data given in Table B1 were used. Since the program was not able to construct a good model in case of repeating experimental points, the mean of the last 12 experimental results, which were the coded experimental points of 0, 0, 0, 0 were taken. Therefore, the total number of experiments used in neural network study was 25. For the training process, 21 of the experiments were chosen and the other 4 of them were used for the comparison test. To reveal the credibility of prediction from ANN selected the response values found by the models constructed by the neural network were compared with the experimental results. For the comparison, graphs were plotted which were showing the experimental results versus the predicted results for both the training data and validation data.

All of the quality parameters calculated by the neural network were found to be highly correlated when compared with the experimental results. Figures 3.18-3.25 show the correlation of experimental quality parameter (weight loss, ΔE value, specific volume, and firmness) with the training and validation data set respectively.

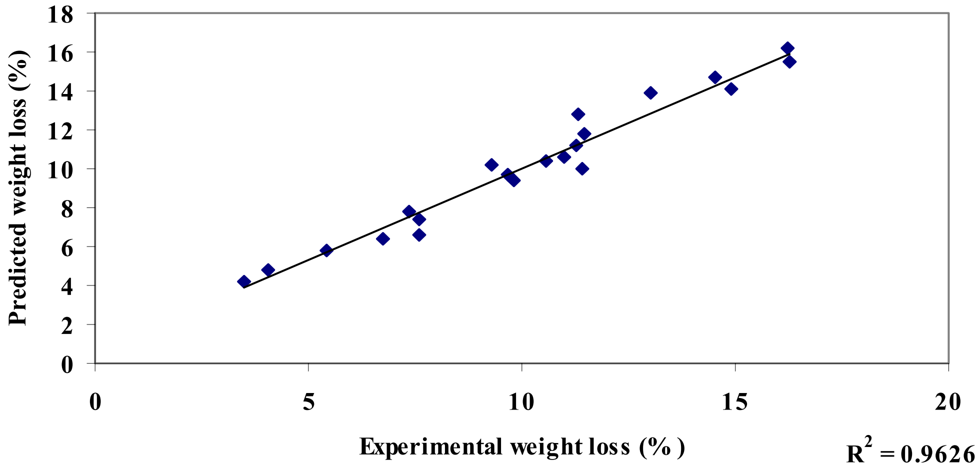


Figure 3.18 Correlation of experimental weight loss versus neural network values of weight loss with training data set

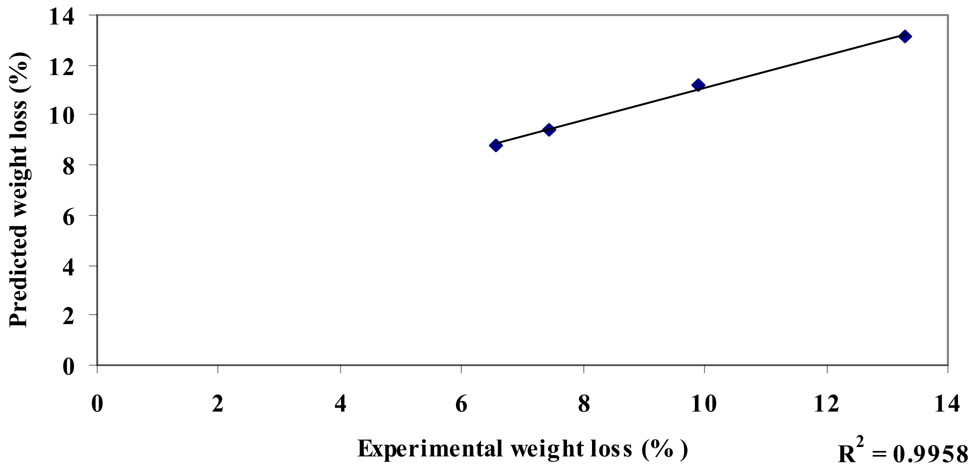


Figure 3.19 Correlation of experimental weight loss versus neural network values of weight loss with validation data set

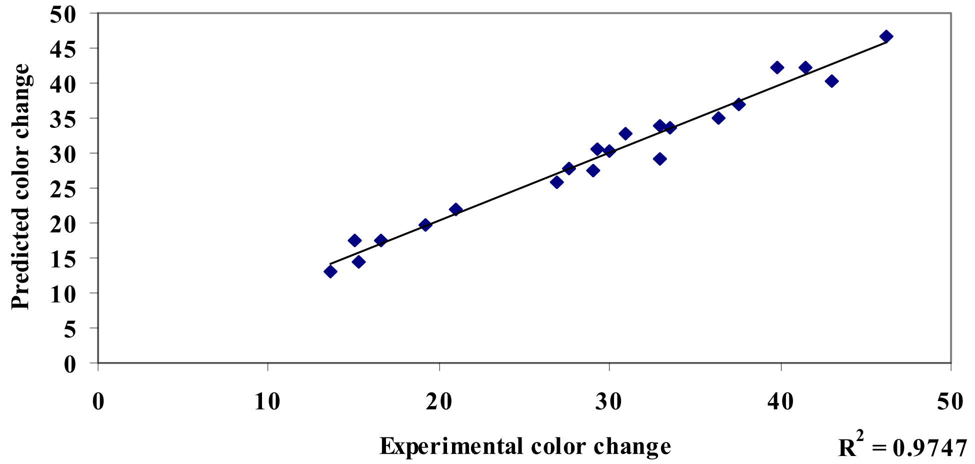


Figure 3.20 Correlation of experimental versus neural network values of color change with training data set

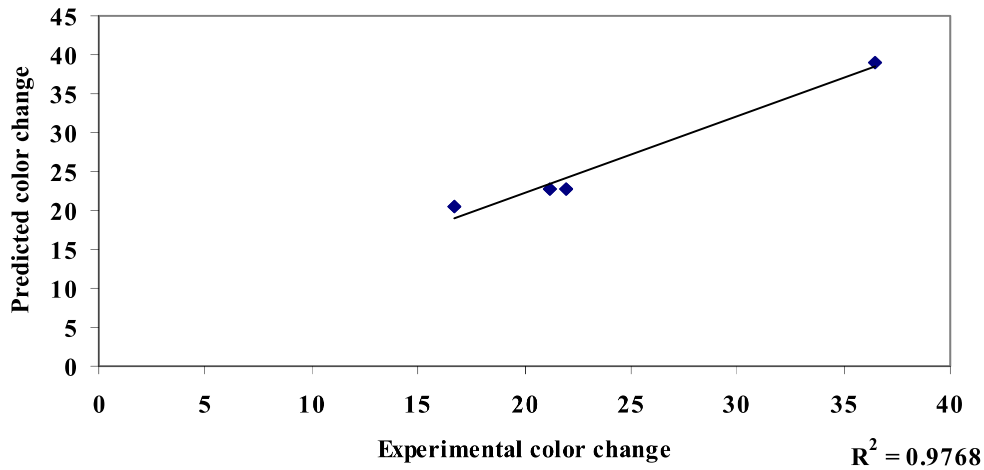


Figure 3.21 Correlation of experimental versus neural network values of color change with validation data set

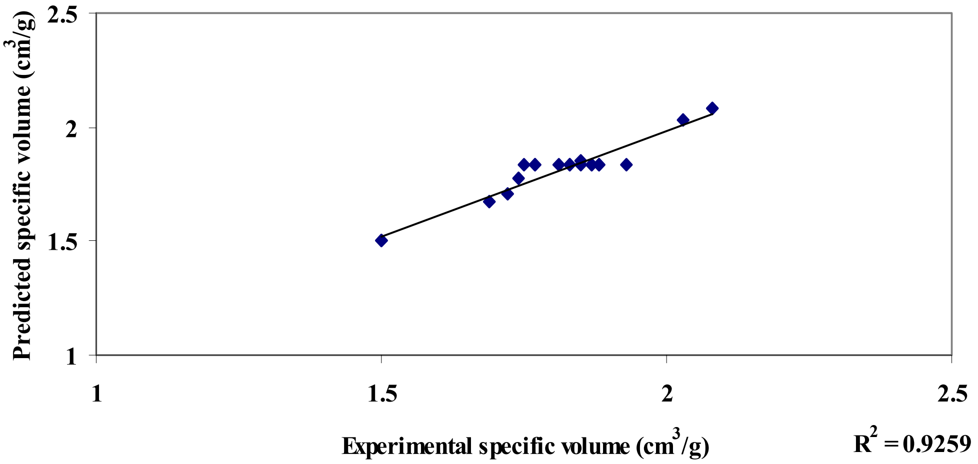


Figure 3.22 Correlation of experimental specific volume versus neural network values of specific volume with training data set

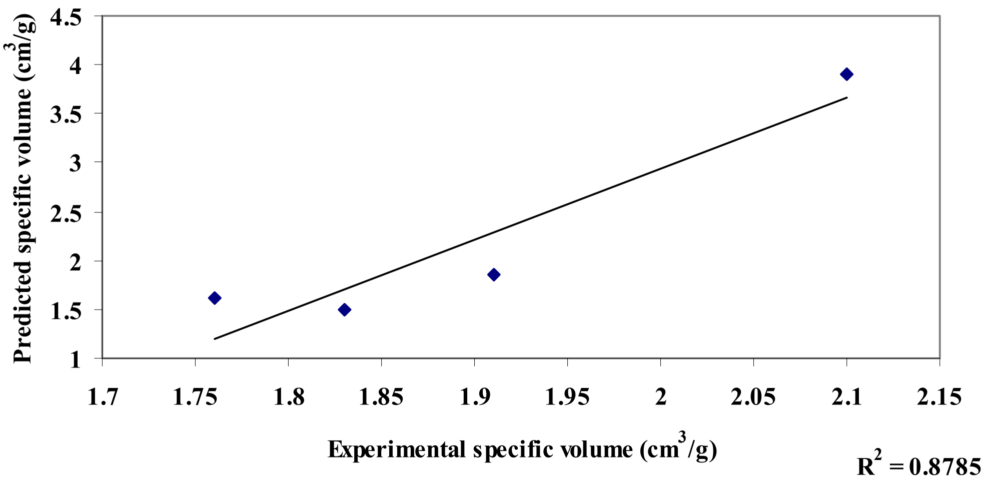


Figure 3.23 Correlation of experimental specific volume versus neural network values of specific volume with validation data set

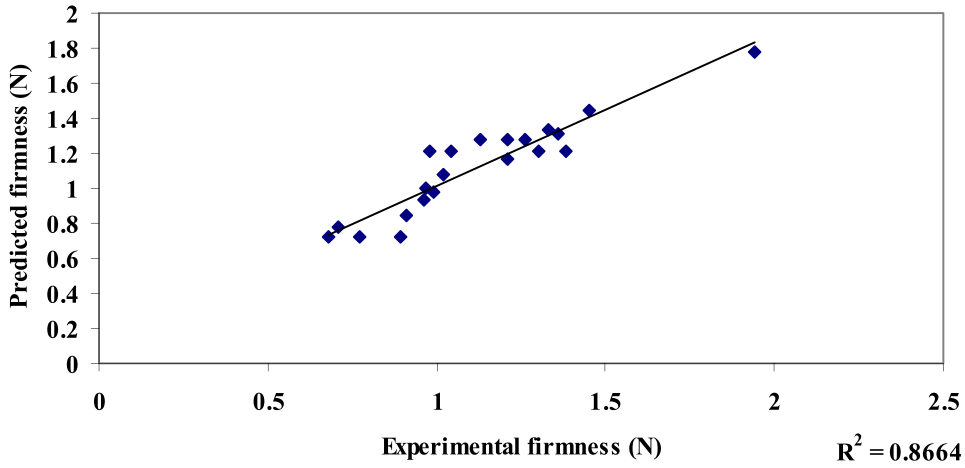


Figure 3.24 Correlation of experimental firmness value versus neural network values of firmness with training data set

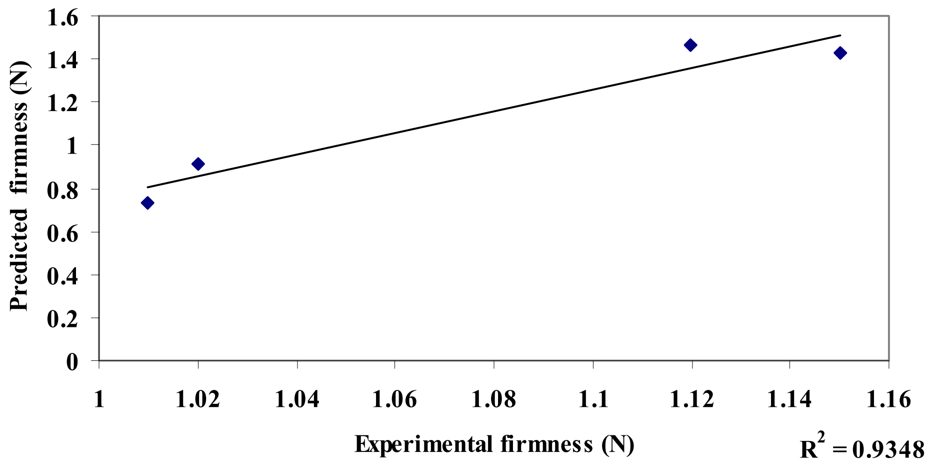


Figure 3.25 Correlation of experimental firmness value versus neural network values of firmness with validation data set

The coefficient of determination values showed that there was a very good agreement especially between the predicted and experimental value of weight loss and ΔE value.

Although the data used for this study were quite sparse, the results were comparable with the RSM study. As can be seen from the Figures 3.18-3.25, the test data gave good results. Therefore, we can say that using neural network even with such a small set of data was feasible. When the coefficient of determinations (r^2) calculated in neural network study for the validation data and RSM study were compared, it was observed that for weight loss and ΔE values, very high values of r^2 were obtained for both of the studies. The coefficient of determinations for specific volume and firmness in both studies had lower values.

The 3-D plots of networks were drawn by keeping two independent variables constant and changing the other two (Fig. 3.26-Fig. 3.29). For weight loss, the constant independents were chosen to be upper and lower halogen lamp powers (Fig. 3.26). In order to make a comparison with the RSM 3-D plots, the constant independents were set to be at the optimum point calculated by RSM.

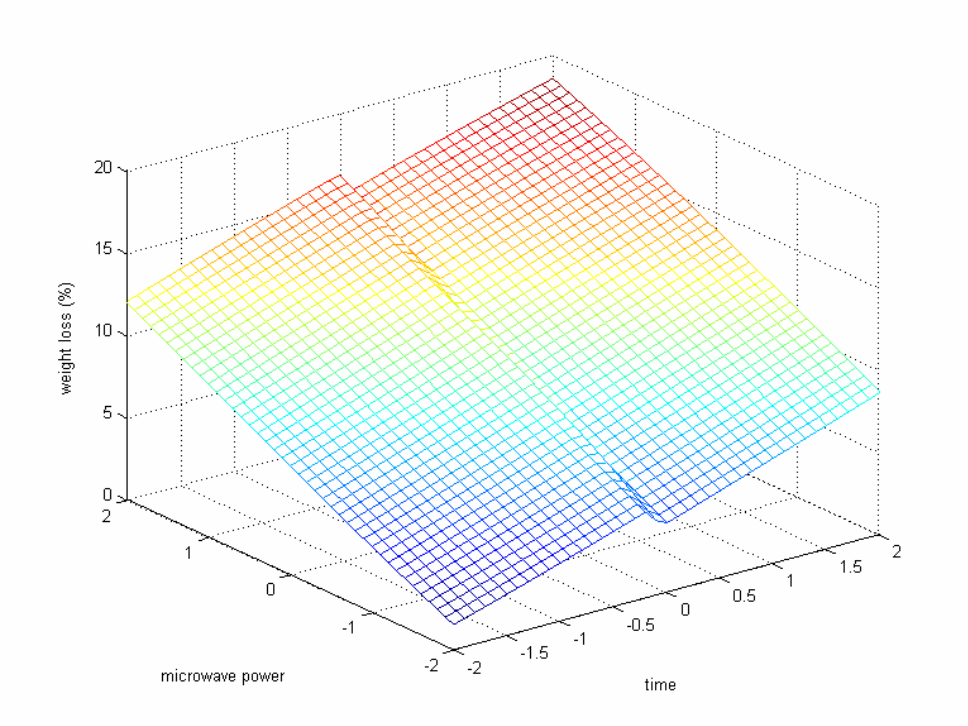


Figure 3.26 Response surfaces for weight loss of breads showing the effects of microwave power and time ($X_2 = 1$, $X_3 = -1$)

From Figure 3.26 it is seen that the same trend as in RSM (Fig. 3.14(b)) was observed. As time and microwave power increased, weight loss increased.

Figure 3.27 shows the ΔE value of breads when baking time and upper halogen lamp were changing. The increase in baking time and upper halogen lamp power increased the color development of the halogen lamp-microwave combination oven baked breads as it was observed in Figure 3.15(a).

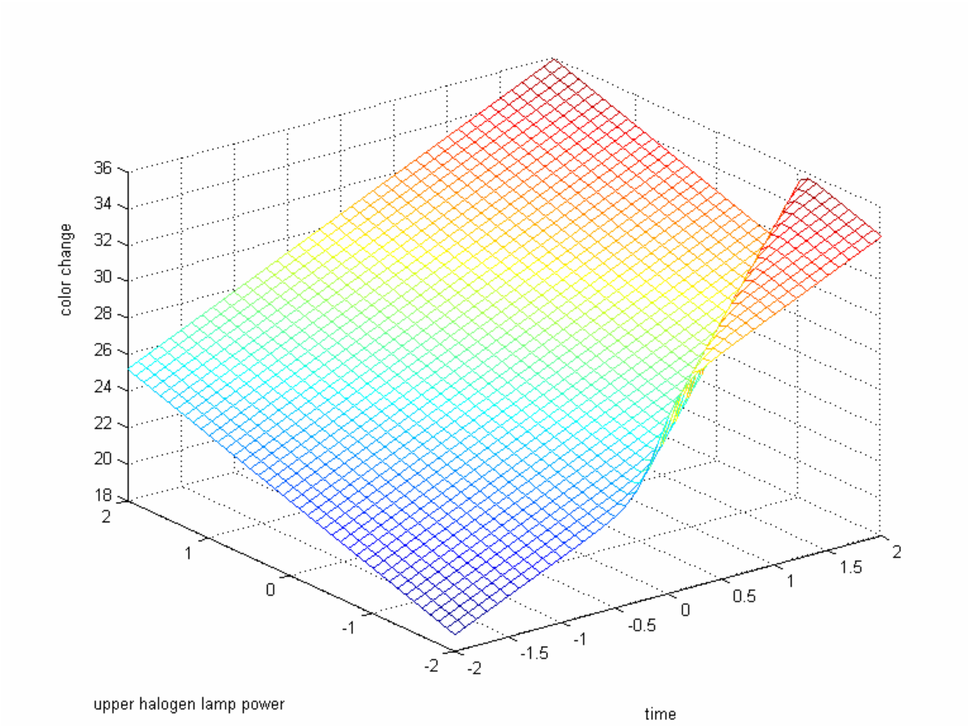


Figure 3.27 Response surfaces for color change of breads showing the effects of upper halogen lamp power and time ($X_3 = -1$, $X_4 = -2$)

For specific volume, when upper and lower halogen lamp powers were kept constant ($X_2 = 1$, $X_3 = -1$ respectively) the increase in microwave power and baking time increased the specific volume of halogen lamp-microwave combination oven baked breads (Fig. 3.28). This trend was also observed in the RSM study (Fig. 3.16), except the fact that Fig 3.16 was smoother.

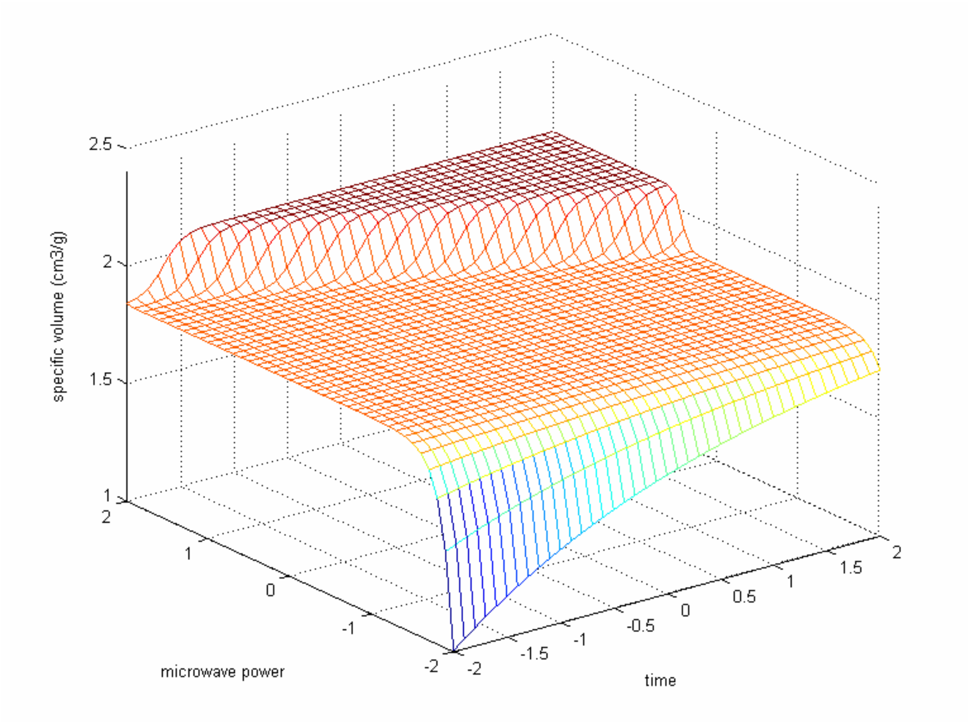


Figure 3.28 Response surfaces for specific volume of breads showing the effects of microwave power and time ($X_2 = 1$, $X_3 = -1$)

Figure 3.29 shows the change of firmness at constant upper and lower halogen lamp powers. The expected trend was obtained but like Figure 3.28, the surface looks non-smooth. The reason for obtaining non-smooth plots may be the few number of data. If the number of data have been more, then smoother surfaces could have been obtained.

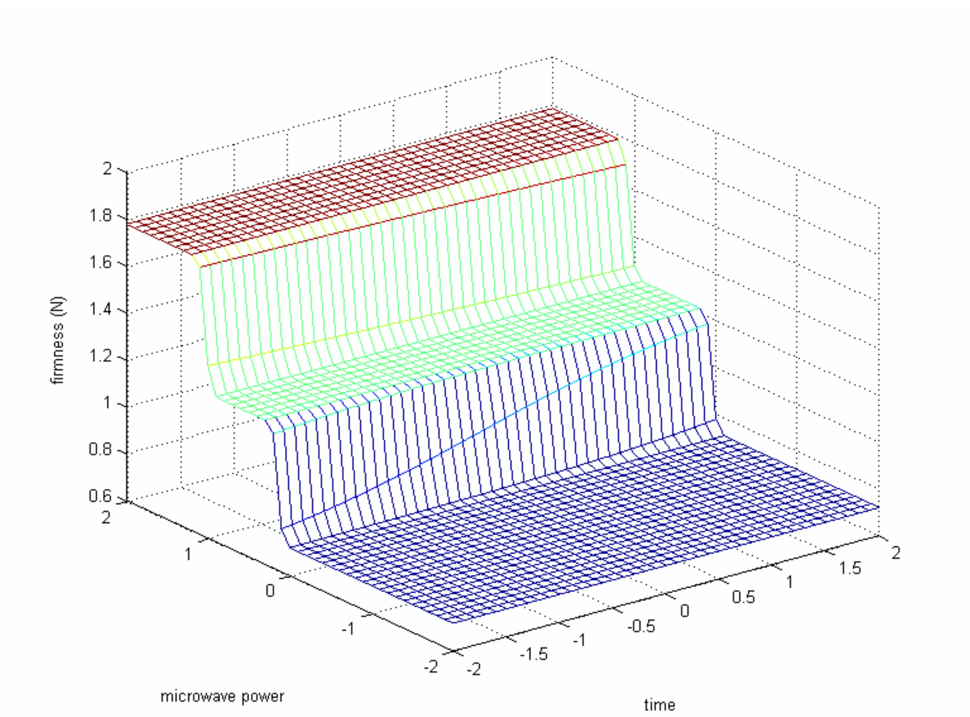


Figure 3.29 Response surfaces for firmness of breads showing the effects of microwave power and time ($X_2 = 1$, $X_3 = -1$)

CHAPTER 4

CONCLUSION AND RECOMMENDATIONS

As time, upper halogen lamp power, and microwave power increased, weight loss of the breads increased. Effects of upper halogen lamp power and time on color change were found to be significant. When time and microwave power increased, higher specific volume was observed. However, the increase in upper halogen lamp power decreased the specific volume of the breads. Time and microwave power were found to be the most significant factors on firmness increase. The lower halogen lamp power was found to be insignificant on affecting all of the quality parameters.

Response surface methodology was successfully applied to optimize the quality of breads baked in halogen lamp-microwave combination oven. The high coefficients of determination of the polynomial models for all of the responses showed that the models were fitted the experimental data well. Breads baked at lower microwave powers and at higher upper halogen lamp powers resulted in less firm and darker colored products when compared to microwave baked breads. Using the halogen lamp-microwave combination oven eliminated the disadvantage of browning problem in microwave baking.

Breads baked in halogen lamp-microwave combination oven at the optimum condition had comparable quality in terms of weight loss, color, specific volume, firmness, chewiness, porosity, and springiness with conventionally baked breads. In addition, conventional baking time of breads was significantly reduced. Therefore, halogen lamp-microwave combination oven can be recommended for bread baking.

Artificial neural network models were developed for each of the quality parameters in order to observe the effects of baking time and different oven conditions on the quality of the breads. Artificial neural network model with one hidden layer and two neurons had a good prediction of all quality parameters during halogen lamp-microwave combination baking. The results were comparable to the RSM study.

Although the quality parameters of the breads were comparable with conventionally baked breads, sensory analysis is recommended in order to make a better comparison both in appearance and eating quality. The gelatinization and retrogradation of starch in breads during halogen lamp-microwave combination baking should be investigated and compared with that of conventional baking.

The possibility of using halogen lamp-microwave combination oven for other baked products that have browning and firmness problem in microwave oven can be investigated to improve product quality and to save time.

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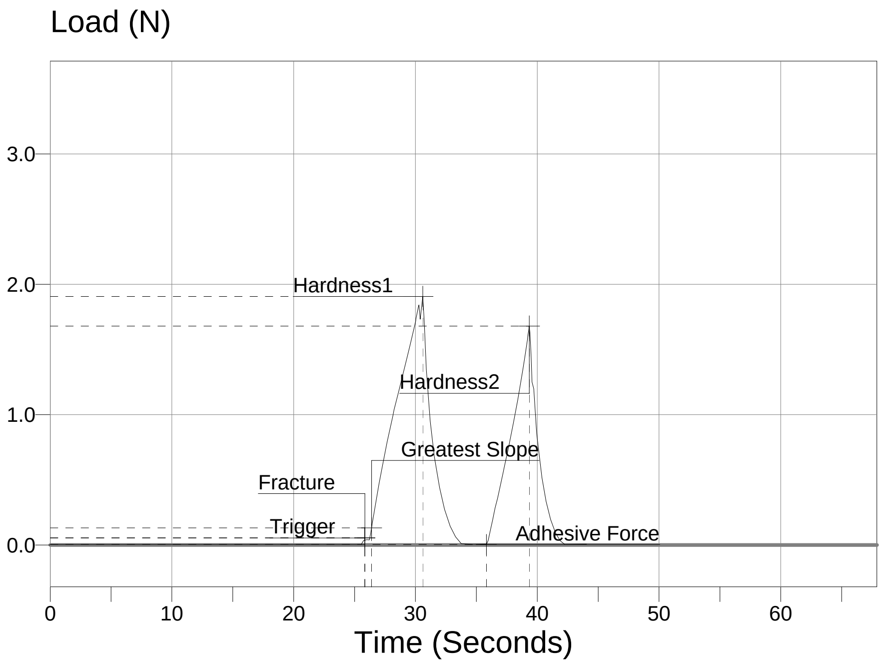
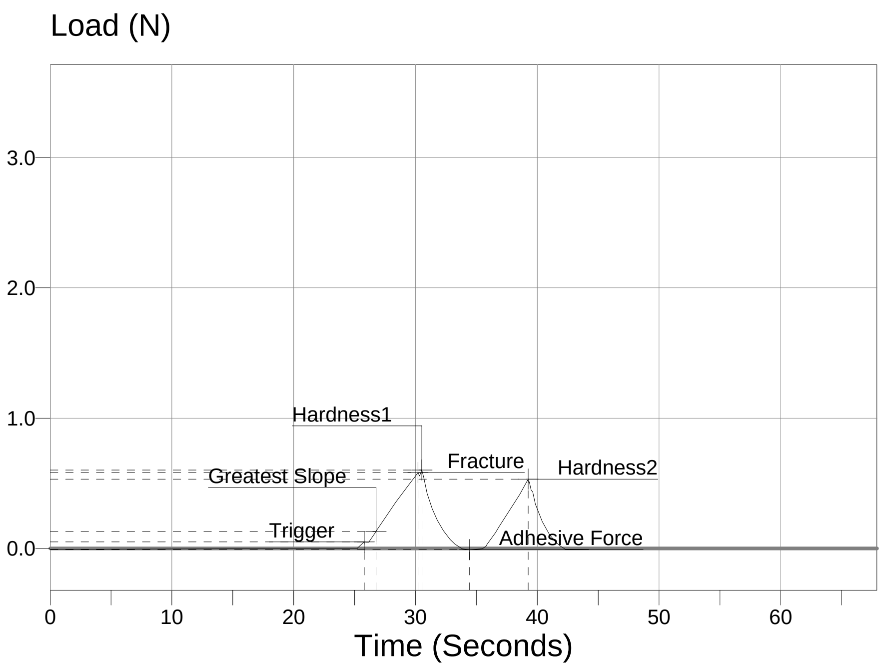
APPENDIX A

A.1 Texture profile of halogen lamp-microwave baked bread (X_1=0, X_2=0, X_3=0, X_4=2)



A.2 Texture profile of halogen lamp-microwave baked bread (X_1=0, X_2=0, X_3=0, X_4=-2)



APPENDIX B

Table B.1 Experimental results for weight loss, ΔE value, specific volume and firmness of the breads

X_1	X_2	X_3	X_4	Weight loss (%)	ΔE value	Sp. volume (cm^3/g)	Firmness (N)
1	1	1	1	16.26	42.99	1.85	1.30
-1	1	1	1	11.31	36.32	1.83	0.98
1	1	1	-1	10.58	41.49	1.87	1.02
1	1	-1	1	14.53	39.84	2.03	1.21
1	-1	1	1	14.92	26.91	2.08	1.33
-1	1	1	-1	7.61	33.51	1.85	0.91
-1	1	-1	1	11.45	37.53	1.88	1.36
-1	-1	1	1	9.88	16.74	1.91	1.12
1	1	-1	-1	7.43	36.45	1.76	1.02
1	-1	1	-1	6.57	21.95	1.83	1.01
1	-1	-1	1	13.29	21.16	2.10	1.15
-1	1	-1	-1	6.74	32.99	1.87	0.77
-1	-1	1	-1	5.43	16.60	1.69	0.89

-1	-1	-1	1	9.29	15.06	1.77	1.45
1	-1	-1	-1	7.35	19.22	1.72	0.96
-1	-1	-1	-1	4.07	15.26	1.50	0.97
0	2	0	0	11.28	46.19	1.93	1.04
0	0	2	0	10.98	30.02	1.75	1.38
0	0	0	2	16.23	29.29	2.08	1.94
2	0	0	0	13.04	30.88	1.81	1.21
0	-2	0	0	9.79	13.64	1.74	1.13
0	0	-2	0	11.42	32.89	1.77	1.26
0	0	0	-2	3.47	27.66	1.50	0.68
-2	0	0	0	7.61	21.03	1.88	0.71
0	0	0	0	9.39	31.48	1.90	1.05
0	0	0	0	9.81	33.10	1.79	0.86
0	0	0	0	9.54	28.84	1.82	0.95
0	0	0	0	8.95	27.68	1.83	0.95
0	0	0	0	9.87	29.68	1.88	1.09
0	0	0	0	10.01	27.62	1.86	1.05
0	0	0	0	10.22	31.37	1.82	0.93
0	0	0	0	9.19	26.91	1.88	0.93
0	0	0	0	9.89	26.88	1.85	0.99
0	0	0	0	9.91	27.92	1.81	0.91
0	0	0	0	9.40	27.30	1.76	1.11
0	0	0	0	10.05	29.91	1.80	1.01

Table B.2 Experimental results for porosity, springiness, and chewiness of the breads

X_1	X_2	X_3	X_4	Porosity	Springiness (mm)	Chewiness (Nmm)
1	1	1	1	66.46	3.06	0.22
-1	1	1	1	67.34	3.02	0.17
1	1	1	-1	70.83	3.06	0.17
1	1	-1	1	68.27	3.07	0.21
1	-1	1	1	66.86	3.05	0.23
-1	1	1	-1	70.07	3.05	0.15
-1	1	-1	1	67.35	2.99	0.23
-1	-1	1	1	67.98	3.02	0.18
1	1	-1	-1	69.37	3.05	0.17
1	-1	1	-1	65.92	3.02	0.17
1	-1	-1	1	66.10	3.09	0.19
-1	1	-1	-1	68.57	3.06	0.13
-1	-1	1	-1	67.16	2.99	0.14
-1	-1	-1	1	66.88	3.07	0.24
1	-1	-1	-1	67.40	3.01	0.16
-1	-1	-1	-1	64.63	3.00	0.15
0	2	0	0	68.02	2.67	0.15
0	0	2	0	68.31	3.04	0.22

0	0	0	2	70.73	3.09	0.33
2	0	0	0	72.41	3.10	0.20
0	-2	0	0	66.36	3.04	0.19
0	0	-2	0	67.30	3.03	0.20
0	0	0	-2	65.27	2.95	0.10
-2	0	0	0	67.72	3.02	0.12
0	0	0	0	68.89	2.99	0.17
0	0	0	0	71.34	3.04	0.15
0	0	0	0	69.02	3.04	0.16
0	0	0	0	67.03	3.01	0.16
0	0	0	0	66.55	3.02	0.18
0	0	0	0	67.70	3.03	0.17
0	0	0	0	66.98	2.95	0.15
0	0	0	0	69.19	3.03	0.15
0	0	0	0	68.32	2.99	0.16
0	0	0	0	67.44	3.03	0.15
0	0	0	0	67.29	3.00	0.15
0	0	0	0	69.13	3.03	0.16

APPENDIX C

REGRESSION TABLES

Table C.1 Regression table for weight loss of breads baked in halogen lamp-microwave combination oven

Dependent variable: Y_1 weight loss

Analysis of Variance

Source	DF	SS	MS	F	p
Regression	14	287.585	20.542	33.15	0.000
Residual Error	21	13.013	0.620		
Total	35	300.598			

Source	DF	Seq SS
X_1	1	53.996
X_2	1	13.605
X_3	1	2.355
X_4	1	207.997
X_1X_1	1	0.065
X_2X_2	1	0.309
X_3X_3	1	2.247
X_4X_4	1	0.164
X_1X_2	1	0.195
X_1X_3	1	0.582
X_1X_4	1	5.052
X_2X_3	1	0.495
X_2X_4	1	0.481
X_3X_4	1	0.040

Predictor	Coef	t	p
Constant	9.6850	42.62	0.000
X_1	1.4999	9.33	0.000
X_2	0.7529	4.69	0.000
X_3	0.3133	1.95	0.065
X_4	2.9439	18.32	0.000
X_1X_1	0.0450	0.32	0.750
X_2X_2	0.0983	0.71	0.488
X_3X_3	0.2650	1.90	0.071
X_4X_4	-0.0717	-0.51	0.612
X_1X_2	-0.1104	-0.56	0.581
X_1X_3	0.1907	0.97	0.343
X_1X_4	0.5619	2.86	0.009
X_2X_3	0.1759	0.89	0.381
X_2X_4	-0.1733	-0.88	0.388
X_3X_4	-0.0501	-0.25	0.801

S = 0.7872 R-Sq = 95.7%

Table C.2 Regression table for ΔE value of breads baked in halogen lamp-microwave combination oven

Dependent variable: Y_2 ΔE value

Analysis of Variance

Source	DF	SS	MS	F	p
Regression	14	2157.54	154.11	36.49	0.000
Residual Error	21	88.68	4.22		
Total	35	2246.22			

Source	DF	Seq SS
X_1	1	179.94
X_2	1	1896.16
X_3	1	7.34
X_4	1	20.78
X_1X_1	1	24.29
X_2X_2	1	0.45
X_3X_3	1	8.13
X_4X_4	1	1.87
X_1X_2	1	1.67
X_1X_3	1	12.83
X_1X_4	1	1.27
X_2X_3	1	0.99
X_2X_4	1	1.82
X_3X_4	1	0.00

Predictor	Coef	t	p
Constant	29.0579	48.98	0.000
X_1	2.7382	6.53	0.000
X_2	8.8886	21.19	0.000
X_3	0.5529	1.32	0.202
X_4	0.9305	2.22	0.038
X_1X_1	-0.8713	-2.40	0.026
X_2X_2	0.1188	0.33	0.747
X_3X_3	0.5040	1.39	0.180
X_4X_4	-0.2415	-0.66	0.513
X_1X_2	-0.3230	-0.63	0.536
X_1X_3	0.8953	1.74	0.096
X_1X_4	0.2819	0.55	0.589
X_2X_3	-0.2493	-0.49	0.633
X_2X_4	0.3371	0.66	0.519
X_3X_4	-0.0159	-0.03	0.976

S = 2.055 R-Sq = 96.1%

Table C.3 Regression table for specific volume of breads baked in halogen lamp-microwave combination oven

Dependent variable: Y_3 specific volume

Analysis of Variance

Source	DF	SS	MS	F	p
Regression	14	0.458296	0.032735	7.06	0.000
Residual Error	21	0.097337	0.004635		
Total	35	0.555634			

Source	DF	Seq SS
X_1	1	0.026678
X_2	1	0.020426
X_3	1	0.002965
X_4	1	0.264515
X_1X_1	1	0.002662
X_2X_2	1	0.001429
X_3X_3	1	0.004607
X_4X_4	1	0.000459
X_1X_2	1	0.038268
X_1X_3	1	0.003441
X_1X_4	1	0.010465
X_2X_3	1	0.019278
X_2X_4	1	0.047490
X_3X_4	1	0.015612

Predictor	Coef	t	p
Constant	1.83344	93.29	0.000
X_1	0.03334	2.40	0.026
X_2	0.02917	2.10	0.048
X_3	0.01112	0.80	0.433
X_4	0.10498	7.55	0.000
X_1X_1	0.00912	0.76	0.457
X_2X_2	0.00668	0.56	0.585
X_3X_3	-0.01200	-1.00	0.330
X_4X_4	-0.00379	-0.31	0.756
X_1X_2	-0.04891	-2.87	0.009
X_1X_3	-0.01467	-0.86	0.399
X_1X_4	0.02557	1.50	0.148
X_2X_3	-0.03471	-2.04	0.054
X_2X_4	-0.05448	-3.20	0.004
X_3X_4	-0.03124	-1.84	0.081

S = 0.06808   R-Sq = 82.5%

Table C.4 Regression table for firmness of breads baked in halogen lamp-microwave combination oven

Dependent variable: Y_4 firmness

Analysis of Variance

Source	DF	SS	MS	F	p
Regression	14	1.52415	0.10887	5.90	0.000
Residual Error	21	0.38769	0.01846		
Total	35	1.91184			

Source	DF	Seq SS
X_1	1	0.10143
X_2	1	0.00955
X_3	1	0.00031
X_4	1	0.98582
X_1X_1	1	0.01238
X_2X_2	1	0.00456
X_3X_3	1	0.15695
X_4X_4	1	0.14885
X_1X_2	1	0.01680
X_1X_3	1	0.05914
X_1X_4	1	0.00969
X_2X_3	1	0.00001
X_2X_4	1	0.00066
X_3X_4	1	0.01800

Predictor	Coef	t	p
Constant	0.98577	25.13	0.000
X_1	0.06501	2.34	0.029
X_2	-0.01994	-0.72	0.480
X_3	-0.00358	-0.13	0.898
X_4	0.20267	7.31	0.000
X_1X_1	-0.01967	-0.82	0.422
X_2X_2	0.01194	0.50	0.624
X_3X_3	0.07003	2.92	0.008
X_4X_4	0.06820	2.84	0.010
X_1X_2	0.03240	0.95	0.351
X_1X_3	0.06080	1.79	0.088
X_1X_4	-0.02460	-0.72	0.477
X_2X_3	0.00088	0.03	0.980
X_2X_4	-0.00643	-0.19	0.852
X_3X_4	-0.03354	-0.99	0.335

S = 0.1359 R-Sq = 79.7%

Table C.5 Regression table for chewiness of breads baked in halogen lamp-microwave combination oven

Dependent variable: Y_5 chewiness

Analysis of Variance

Source	DF	SS	MS	F	p
Regression	14	0.0504231	0.0036017	7.72	0.000
Residual Error	21	0.0098000	0.0004667		
Total	35	0.0602231			

Source	DF	Seq SS
X_1	1	0.0036862
X_2	1	0.0002861
X_3	1	0.0000011
X_4	1	0.0332298
X_1X_1	1	0.0000639
X_2X_2	1	0.0000764
X_3X_3	1	0.0045110
X_4X_4	1	0.0055777
X_1X_2	1	0.0003974
X_1X_3	1	0.0018955
X_1X_4	1	0.0002103
X_2X_3	1	0.0000107
X_2X_4	1	0.0000000
X_3X_4	1	0.0004770

Predictor	Coef	t	p
Constant	0.159527	25.58	0.000
X_1	0.012393	2.81	0.010
X_2	-0.003453	-0.78	0.442
X_3	-0.000215	-0.05	0.962
X_4	0.037210	8.44	0.000
X_1X_1	-0.001414	-0.37	0.715
X_2X_2	0.001545	0.40	0.690
X_3X_3	0.011873	3.11	0.005
X_4X_4	0.013202	3.46	0.002
X_1X_2	0.004984	0.92	0.367
X_1X_3	0.010884	2.02	0.057
X_1X_4	-0.003626	-0.67	0.509
X_2X_3	-0.000817	-0.15	0.881
X_2X_4	-0.000000	-0.00	1.000
X_3X_4	-0.00546	-1.01	0.324

S = 0.02160 R-Sq = 83.7%

Table C.6 Regression table for porosity of breads baked in halogen lamp-microwave combination oven

Dependent variable: Y_6 porosity

Analysis of Variance

Source	DF	SS	MS	F	p
Regression	21	74.446	3.545	2.01	0.091
Residual Error	14	24.685	1.763		
Total	35	99.132			

Source	DF	Seq SS
X_1	1	4.679
X_2	1	14.516
X_3	1	1.528
X_4	1	0.732
X_1X_1	1	3.737
X_2X_2	1	4.567
X_3X_3	1	1.600
X_4X_4	1	0.986
X_1X_2	1	0.245

X_1X_3	1	2.405
X_1X_4	1	1.522
X_2X_3	1	0.192
X_2X_4	1	9.212
X_3X_4	1	0.975
$X_1X_1X_1$	1	6.396
$X_2X_2X_2$	1	1.579
$X_3X_3X_3$	1	0.000
$X_1X_2X_3$	1	0.393
$X_1X_2X_4$	1	0.228
$X_2X_3X_4$	1	1.955
$X_4X_1X_1$	1	16.999

Predictor	Coef	t	p
Constant	68.2404	178.02	0.000
X_1	-0.2885	-0.61	0.549
X_2	1.1404	2.43	0.029
X_3	0.2540	0.54	0.597
X_4	1.3649	2.91	0.011
X_1X_1	0.3417	1.46	0.167
X_2X_2	-0.3778	-1.61	0.130

X_3X_3	-0.2236	-0.95	0.357
X_4X_4	-0.1755	-0.75	0.467
X_1X_2	0.1238	0.37	0.715
X_1X_3	-0.3877	-1.17	0.262
X_1X_4	-0.3085	-0.93	0.369
X_2X_3	-0.1096	-0.33	0.746
X_2X_4	-0.7588	-2.29	0.038
X_3X_4	-0.2469	-0.74	0.469
$X_1X_1X_1$	0.3650	1.90	0.078
$X_2X_2X_2$	-0.1814	-0.95	0.360
$X_3X_3X_3$	-0.0008	-0.00	0.997
$X_1X_2X_3$	0.1566	0.47	0.644
$X_1X_2X_4$	0.1193	0.36	0.725
$X_2X_3X_4$	-0.3496	-1.05	0.310
$X_4X_1X_1$	-1.7853	-3.10	0.008

S = 1.328   R-Sq = 75.1%

Table C.7 Regression table for springiness of breads baked in halogen lamp-microwave combination oven

Dependent variable: Y_7 springiness

Analysis of Variance

Source	DF	SS	MS	F	p
Regression	21	0.147047	0.007002	4.90	0.002
Residual Error	14	0.019991	0.001428		
Total	35	0.167037			

Source	DF	Seq SS
X_1	1	0.004845
X_2	1	0.016718
X_3	1	0.000010
X_4	1	0.006973
X_1X_1	1	0.011460
X_2X_2	1	0.032712
X_3X_3	1	0.005576
X_4X_4	1	0.003464
X_1X_2	1	0.000071

X_1X_3	1	0.000018
X_1X_4	1	0.000878
X_2X_3	1	0.000791
X_2X_4	1	0.004917
X_3X_4	1	0.000344
$X_1X_1X_1$	1	0.000363
$X_2X_2X_2$	1	0.052263
$X_3X_3X_3$	1	0.000277
$X_1X_2X_3$	1	0.000271
$X_1X_2X_4$	1	0.000589
$X_2X_3X_4$	1	0.000545
$X_4X_1X_1$	1	0.003962

Predictor	Coef	t	p
Constant	3.01317	276.23	0.000
X_1	0.00871	0.65	0.525
X_2	0.03960	2.96	0.010
X_3	-0.00545	-0.41	0.689
X_4	0.03522	2.64	0.020
X_1X_1	0.018924	2.83	0.013
X_2X_2	-0.031973	-4.79	0.000

X_3X_3	0.013200	1.98	0.068
X_4X_4	0.010405	1.56	0.142
X_1X_2	0.002105	0.22	0.827
X_1X_3	0.001055	0.11	0.913
X_1X_4	0.007406	0.78	0.446
X_2X_3	0.007031	0.74	0.469
X_2X_4	-0.017531	-1.86	0.085
X_3X_4	-0.004636	-0.49	0.631
$X_1X_1X_1$	0.002752	0.50	0.622
$X_2X_2X_2$	-0.032997	-6.05	0.000
$X_3X_3X_3$	0.002403	0.44	0.666
$X_1X_2X_3$	-0.004114	-0.44	0.670
$X_1X_2X_4$	0.006067	0.64	0.531
$X_2X_3X_4$	0.005834	0.62	0.547
$X_4X_1X_1$	-0.02726	-1.67	0.118

S = 0.03779 R-Sq = 88.0%

APPENDIX D

DUNCAN AND ANOVA TABLES

Table D.1 ANOVA and Duncan's Multiple Range Test Table for weight loss of halogen lamp-microwave combination oven baked breads

General Linear Models Procedure

Class	Levels	Values				
X_1	5	0	1	2	-1	-2
X_2	5	0	1	2	-1	-2
X_3	5	0	1	2	-1	-2
X_4	5	0	1	2	-1	-2

Number of observations in data set = 36

X_1 : Time of baking, X_2 : Upper halogen lamp power, X_3 : Lower halogen lamp power, X_4 : Microwave power

Source	DF	Sum of Squares	Mean Square	F Value	$p_r > F$
Model	19	294.96545833	15.52449781	43.67	0.0001
Error	16	5.68761667	0.355476041		
Total	35	300.65307500			

Dependent Variable : Y_1 Weight Loss

Duncan's Multiple Range test for variable Y_1

Alpha = 0.05

Means with the same letter are not significantly different.

Duncan Grouping	Mean	N	X_1
A	13.0400	1	2
B	11.3663	8	1
C	9.9678	18	0
D	8.2238	8	-1
D	7.6100	1	-2

Duncan Grouping	Mean	N	X_2
A	11.2800	1	2
AB	10.7387	8	1
BC	9.9444	18	0
BC	9.7900	1	-2
C	8.8513	8	-1

Duncan Grouping	Mean	N	X_3
A	11.4200	1	-2
AB	10.9800	1	2
ABC	10.3200	8	1
BC	9.8706	18	0
C	9.2700	8	-1

Duncan Grouping	Mean	N	X_4
A	16.2300	1	2
B	12.6175	8	1
C	10.0200	18	0
D	6.9725	8	-1
E	3.4800	1	-2

Table D.2 ANOVA and Duncan's Multiple Range Test Table for ΔE values of halogen lamp-microwave combination oven baked breads

General Linear Models Procedure

Class	Levels	Values				
X_1	5	0	1	2	-1	-2
X_2	5	0	1	2	-1	-2
X_3	5	0	1	2	-1	-2
X_4	5	0	1	2	-1	-2

Number of observations in data set = 36

X_1 : Time of baking, X_2 : Upper halogen lamp power, X_3 : Lower halogen lamp power, X_4 : Microwave power

Source	DF	Sum of Squares	Mean Square	F Value	$p_r > F$
Model	19	2189.43677500	115.2335145	32.55	0.0001
Error	16	56.64250000	3.54015625		
Total	35	2246.07927500			

Dependent Variable : Y_2 ΔE values

Duncan's Multiple Range test for variable Y_2

Alpha = 0.05

Means with the same letter are not significantly different.

Duncan Grouping	Mean	N	X_1
A	31.251	8	1
A	30.880	1	2
A	29.354	18	0

B	25.501	8	-1
C	21.030	1	-2

Duncan Grouping	Mean	N	X_2
A	46.190	1	2
B	37.640	8	1
C	28.914	18	0
D	19.113	8	-1
E	13.640	1	-2

Duncan Grouping	Mean	N	X_3
A	32.890	1	-2
AB	30.020	1	2
AB	29.564	8	1
B	28.743	18	0
B	27.189	8	-1

Duncan Grouping	Mean	N	X_4
A	29.569	8	1
A	29.290	1	2
A	29.074	18	0
A	27.660	1	-2
A	27.184	8	-1

Table D.3 ANOVA and Duncan's Multiple Range Test Table for specific volume of halogen lamp-microwave combination oven baked breads

General Linear Models Procedure

Class	Levels	Values				
X_1	5	0	1	2	-1	-2
X_2	5	0	1	2	-1	-2
X_3	5	0	1	2	-1	-2
X_4	5	0	1	2	-1	-2

Number of observations in data set = 36

X_1 : Time of baking, X_2 : Upper halogen lamp power, X_3 : Lower halogen lamp power, X_4 : Microwave power

Source	DF	Sum of Squares	Mean Square	F Value	$p_r > F$
Model	19	0.52455833	0.027608333	12.98	0.0001
Error	16	0.03404167	0.0021276048		
Total	35	0.55860000			

Dependent Variable : Y_3 specific volume

Duncan's Multiple Range test for variable Y_3

Alpha = 0.05

Means with the same letter are not significantly different.

Duncan Grouping	Mean	N	X_1
A	1.90500	8	1
AB	1.88000	1	-2
AB	1.82056	18	0

AB	1.81000	1	2
B	1.78750	8	-1

Duncan Grouping	Mean	N	X_2
A	1.93000	1	2
AB	1.86750	8	1
BC	1.82500	8	-1
BC	1.82167	18	0
C	1.74000	1	-2

Duncan Grouping	Mean	N	X_3
A	1.86375	8	1
AB	1.83000	18	0
AB	1.82875	8	-1
AB	1.77000	1	-2
B	1.75000	1	2

Duncan Grouping	Mean	N	X_4
A	2.08000	1	2
B	1.93125	8	1
C	1.82667	18	0
C	1.76125	8	-1
D	1.50000	1	-2

Table D.4 ANOVA and Duncan's Multiple Range Test Table for firmness of halogen lamp-microwave combination oven baked breads

General Linear Models Procedure

Class	Levels	Values				
X_1	5	0	1	2	-1	-2
X_2	5	0	1	2	-1	-2
X_3	5	0	1	2	-1	-2
X_4	5	0	1	2	-1	-2

Number of observations in data set = 36

X_1 : Time of baking, X_2 : Upper halogen lamp power, X_3 : Lower halogen lamp power, X_4 : Microwave power

Source	DF	Sum of Squares	Mean Square	F Value	$p_r > F$
Model	19	1.76729097	0.093015314	10.48	0.0001
Error	16	0.14207292	0.0088795575		
Total	35	1.90936389			

Dependent Variable : Y_4 firmness

Duncan's Multiple Range test for variable Y_4

Alpha = 0.05

Means with the same letter are not significantly different.

Duncan Grouping	Mean	N	X_1
A	1.21000	1	2
A	1.12500	8	1
A	1.07000	18	0

A	1.05625	8	-1
B	0.71000	1	-2

Duncan Grouping	Mean	N	X_2
A	1.13000	1	-2
A	1.11000	8	-1
A	1.07125	8	1
A	1.05611	18	0
A	1.04000	1	2

Duncan Grouping	Mean	N	X_3
A	1.38000	1	2
AB	1.26000	1	-2
BC	1.11125	8	-1
BC	1.07000	8	1
C	1.03000	18	0

Duncan Grouping	Mean	N	X_4
A	1.94000	1	2
B	1.23750	8	1
C	1.03111	18	0
C	0.94375	8	-1
D	0.68000	1	-2

APPENDIX E

The Matlab Program was used to find the optimum baking condition in halogen lamp-microwave combination oven. For this purpose, the following Matlab line was used.

```
x0=[0 0 0 0]';[x,fval,exitflag]=fmincon('f',x0,[],[],[],[],[-2 -2 -2 -2]',[2 2 2 2]','nonlincon')
```

In this line x0 determines the starting initial point of the optimization problem. "fmincon" is a Matlab program that minimizes a nonlinear function of several variables with some equality or inequality, linear or nonlinear constraints. More precisely FMINCON solves problems of the form:

$$
\begin{aligned}
&Min\ f(x) \\
&Ax \leq b, \quad A_{eq}x = b_{eq} \\
&C(x) \leq 0, \quad C_{eq}(x) = 0 \\
&lb \leq x \leq ub
\end{aligned}
$$

where $C(x) \leq 0$ and $C_{eq}(x) = 0$ are nonlinear constraints and *lb* and *ub* are the upper and lower bounds for the variables in the vector form. In this study, nonlinear constraints were named as "nonlincon".

The arguments of 'fmincon' that were used in this study were 'f' that represented the function minimized, x0 which was the initial point, and the symbol [] that denoted the empty values for A, b, A_{eq}, and b_{eq} values. The other arguments were the two 4 dimensional vectors which represented the upper and lower bonds, and 'nonlincon' was the nonlinear constraint of the presentation.

The factors ‘nonlincon’ and ‘f’ were defined by the following routines written for the problem:

1.Function ‘nonlincon’: This function defined the nonlinear constraint, namely color change value that should be in between the values of 35.9-47.7.

```
function [c,a]=nonlincon(x)

qwl=[0.045 -0.11/2 0.191/2 0.562/2;-0.11/2 0.098 0.176/2 -0.173/2; 0.191/2
0.176/2 0.265 -0.05/2; 0.562/2 -0.173/2 -0.05/2 -0.072];

bwl=[1.5 0.753 0.313 2.94]';

cwl=9.69;

wl=x'*qwl*x+x'*bwl+cwl;

qc=[-0.871 -0.323/2 0.895/2 0.282/2; -0.323/2 0.119 -0.249/2 0.337/2;0.895/2
-0.249/2 0.504 -0.016/2; 0.282/2 0.337/2 -0.016/2 -0.242];

bc=[2.74 8.89 0.553 0.93]';

cc=29.1;

col=x'*qc*x+x'*bc+cc;

c=[col-47.7 -col+35.9 wl-4.5 -wl]'

a=[];
```

2. Function ‘f’: This function is the function that FMINCON minimized according to the constraints ‘nonlincon’ and upper and lower values of the independent variables.

```
function [y]=f(x)

lambda=1;

qt=[-0.00197*10 0.00324/2*10 0.00608/2*10 -0.00246/2*10;0.00324/2*10
0.00119*10 0.00009/2*10 -0.00064*10; 0.00608/2*10 0.00009/2*10 0.007*10
-0.00335/2*10; -0.00246/2*10 -0.00064/2*10 -0.00335/2*10 0.00682*10];
```

```
bt=[0.0065*10 -0.00198*10 -0.00036*10 0.0203*10]';
ct=0.0986*10;
qv=[0.0091 -0.0489/2 -0.0147/2 0.0256/2; -0.0489/2 0.0067 -0.0347/2 -0.0545/2;
   -0.0147/2 -0.0347/2 -0.0120 -0.0312/2;0.0256/2 -0.0545/2 -0.0312/2 -0.0038 ];
bv=[0.0333 0.0292 0.0111 0.105]';
cv=1.83;
y=x'*qt*x+x'*bt+ct-lambda*(x'*qv*x+x'*bv+cv);
```

Here ‘qwl’, ‘bwl’, ‘cwl’, and ‘wl’, ‘qc’, ‘bc’, ‘cc’, and ‘col’ are used to define the second order equations of weight loss and color respectively in terms of a matrix, i.e. “wl” stands for weight loss and “c” and “col” stands for color (ΔE value). ‘qwl’ and ‘qc’ represent the matrix written for the second order terms (X_1^2, X_2^2, X_3^2, X_4^2) and the interaction terms (X_1X_2, X_1X_3, X_1X_4, X_2X_3, X_2X_4, X_3X_4). ‘bwl’ and ‘bc’ are the matrices defined for the first order terms (X_1, X_2, X_3, and X_4) and ‘cwl’ and ‘cc’ are the constant terms in the second order polynomial fitted for the parameters of weight loss and ΔE value respectively. ‘wl’ and ‘col’ are the total equations representing the weight loss and ΔE value.

‘qt’, ‘bt’, ‘ct’, and ‘qv’, ‘bv’, ‘cv’ are used to define the second order equations of firmness and specific volume respectively. Here again, ‘qt’ and ‘qv’ represent the matrix written for the second order terms and the interaction terms. ‘bt’ and ‘bv’ are the matrices defined for the first order terms and ‘ct’ and ‘cv’ are the constant terms in the second order polynomial fitted for the parameters of firmness and specific volume respectively. ‘y’ is the total equation that is minimized in order to obtain minimum firmness and maximum specific volume.

APPENDIX F

In this part, the Matlab Program written for the neural network study and the calculated weight and bias functions are given. The program is only explained for the weight loss. The neural networks for the other parameters were constructed in the same way.

Weight Loss

In order to construct the neural network, the following Matlab line was used:

[Wwl,Bwl,YMwl,netwl]=weightlossdnm(P);

In this line, ‘W’and ‘B’ are the symbols used to represent weight and bias functions. ‘YM’ is the surface that was constructed to see the calculated points when two independents kept constant and two changing, and ‘net’ is the constructed network for the weight loss. The ‘wl’ are used to mention the weight loss. P is the matrix that represented the experimental points used in the study. The defined function to construct the network is given below:

function [Wwl,Bwl,YMwl,netwl]=weightlossdnm(PM);

% L represents the experimental data at the experiment points given by PM

L=[16.26 11.31 10.58 14.53 14.92 7.61 11.45 6.74 5.43 9.29 7.35 4.07 11.28 10.98 16.23 13.04 9.79 11.42 3.47 7.61 9.69];

%newff is a Matlab function that generates a feed-forward neural network according to the description given in the arguments. First argument is a matrix that defines the upper and lower bounds for the independent variables. 2 is the number of nodes and 1 is the number of hidden layers. ‘tansig’ and ‘purelin’ are the transfer functions used in the construction of the network.

```
netwl=newff([-2 2;-2 2;-2 2;-2 2],[2 1],{'tansig','purelin'});

%‘train’ is a MATLAB function that trains the generated set by the ‘newff’.

netwl=train(netwl,PM,L);

YMwl=[];

for k=1:41, PP=[[-2:.1:2];ones(1,41);-1*ones(1,41);(-2+(k-1)*.1)*ones(1,41)];


YMwl=[YMwl;sim(netwl,PP)];

end;

mesh(YMwl)

%the following variables are the parameters of the trained neural net. W is for the weight function and B is for the bias function.

Wwl=netwl.iw{1,1};

Bwl=netwl.b{1};

function YMwl=weightlosssim(netwl);

YMwl=[];

for k=1:41, PP=[[-2:.1:2];zeros(1,41);0*ones(1,41);(-2+(k-1)*.1)*ones(1,41)];

   YMwl=[YMwl;sim(netwl,PP)];

end;

mesh(YMwl)
```

Color change (ΔE value)

```
function [WC,BC,YMC,netC]=colordnm(PM);
C=[42.99 36.32 41.49 39.84 26.91 33.51 37.53 32.99 16.60 15.06 19.22 15.26
46.20 30.02 29.29 30.88 13.64 32.89 27.66 21.03 29.06];
netC=newff([-2 2;-2 2;-2 2;-2 2],[4 1],{'tansig','purelin'});
netC=train(netC,PM,C);
YMC=[];
for k=1:41, PP=[[-2:.1:2];(-2+(k-1)*.1)*ones(1,41);-1*ones(1,41);-
2*ones(1,41)];
   YMC=[YMC;sim(netC,PP)];
end;
mesh(YMC)
WC=netC.iw{1,1};
BC=netC.b{1};

function YMC=colorsim(netC);
YMC=[];
for k=1:41, PP=[[-2:.1:2];zeros(1,41);0*ones(1,41);(-2+(k-1)*.1)*ones(1,41)];
   YMC=[YMC;sim(netC,PP)];
end;
mesh(YMC)
```

Specific Volume

```
function [WV,BV,YMV,netV]=volumednm(PM);
V=[1.85 1.83 1.87 2.03 2.08 1.85 1.88 1.87 1.69 1.77 1.72 1.50 1.93 1.75 2.08
1.81 1.74 1.77 1.50 1.88 1.83];
netV=newff([-2 2;-2 2;-2 2;-2 2],[2 1],{'tansig','purelin'});
netV=train(netV,PM,V);
YMV=[];
for k=1:41, PP=[[-2:.1:2];ones(1,41);-1*ones(1,41);(-2+(k-1)*.1)*ones(1,41)];
   YMV=[YMV;sim(netV,PP)];
end;
mesh(YMV)
WV=netV.iw{1,1};
BV=netV.b{1};

function YMV=volumesim(netV);
YMV=[];
for k=1:41, PP=[[-2:.1:2];zeros(1,41);0*ones(1,41);(-2+(k-1)*.1)*ones(1,41)];
   YMV=[YMV;sim(netV,PP)];
end;
mesh(YMV)
```

Firmness

```
function [WF,BF,YMF,netF]=firmnessdnm(PM);
F=[1.3 0.98 1.02 1.21 1.33 0.91 1.36 0.77 0.89 1.45 0.96 0.97 1.04 1.38 1.94
1.21 1.13 1.26 0.68 0.71 0.99];
netF=newff([-2 2;-2 2;-2 2;-2 2],[4 1],{'tansig','purelin'});
netF=train(netF,PM,F);
YMF=[];
for k=1:41, PP=[[-2:.1:2];zeros(1,41);0*ones(1,41);(-2+(k-1)*.1)*ones(1,41)];
   YMF=[YMF;sim(netF,PP)];
end;
mesh(YMF)
WF=netF.iw{1,1};
BF=netF.b{1};


function YMF=firmnesssim(netF);
YMF=[];
for k=1:41, PP=[zeros(1,41);[-2:.1:2];-1*ones(1,41);(-2+(k-1)*.1)*ones(1,41)];
   YMF=[YMF;sim(netF,PP)];
end;
mesh(YMF)
```

Weight and Bias Functions

Weight loss

Wwl =

0.1028	0.0379	0.0229	0.1255
-37.8527	-12.7842	-6.2809	1.4088

Bwl =

0.0700

-1.2390

Color change

WC =

0.0257	0.0705	0.0146	0.0153
4.6340	27.9215	-15.3867	-8.7140

BC =

-0.0180

-16.9791

Specific volume

WV1 =

1.5083	-1.5976	-1.5899	1.5647
2.1597	-8.3093	-6.3453	-4.1545

BV1 =

-4.2783

-4.0331

Firmness

WF1 =

-0.0785	0.1092	0.0036	-0.2058
3.5464	-5.8343	0.9501	1.2118

BF1 =

1.7796

-7.4344