ADVANCES IN MACHINERY AND DIGITIZATION

EDITOR
Merivan ŞAŞMAZ
CONTENTS

PREFACE

Assist. Prof. Dr. Merivan ŞAŞMAZ............................................................1

CHAPTER 1
SIMULTANEOUS OPTIMIZATION OF BURNISHING PARAMETERS USING MULTI-OBJECTIVE TAGUCHI TECHNIQUE

Prof. Dr. Funda KAHRAMAN & Res. Assist. Gokhan BASAR............. 3

CHAPTER 2
IMPROVED OPTIMUM PID CONTROLLER TUNING BY MINIMIZING SETTLING TIME AND OVERSHOOT

Assist Prof. Dr. Abdullah TURAN ..............................................................29

CHAPTER 3
OPTIMIZATION OF MACHINING PARAMETERS IN TURNING OF AISI 4340 STEEL

Doç. Dr. Mustafa ÖZDEMİR & Öğr. Gör. Ömer TÜRKCAN

Doç. Dr. Volkan YILMAZ & Dr. Öğr. Üyesi Mohammad Rafighi

.............................................................................................................51
CHAPTER 4
A NOVEL IMAGE SEGMENTATION TECHNIQUE FOR MEDICAL DECISION SUPPORT SYSTEMS: OSTEOARTHRITIS (OA) KNEE ABNORMALITY DETECTION FROM HAZY X-RAY IMAGES THROUGH POLYGON CONSTRUCTION BASED ON CONNECTED LINE SEGMENTS

Ibrahim Furkan INCE & Faruk BULUT

CHAPTER 5
REMOTE MONITORING OF MUSCLE SIGNALS WITH EMG SENSOR

Öğr. Gör. Çağatay ERSİN

CHAPTER 6
IMPROVED PERFORMANCE OF YEAST LOCALIZATION PREDICTION BY BALANCING WITH DBSCAN AND WEIGHTED ARITHMETIC MEAN

Assist. Prof. Serkan GÜLDAL

CHAPTER 7
NUMERICAL EVALUATION OF EXPERIMENTAL RESULTS FOR BURIED PIPES IN GEOSYNTHETIC REINFORCED SAND

Res. Assist. Dr. Güneş BABAGİRAY
CHAPTER 8
USE OF EXHAUST VALVE PHASE SHIFT METHOD FOR ACCELERATED EXHAUST AFTER-TREATMENT HEAT-UP IN HEAVY-DUTY DIESEL VEHICLES

Res. Ass. Dr. Hasan Üstün BAŞARAN ..............................................191
ÖN SÖZ

Machinery has advanced human lives since ancient days. Similarly, by the digitization of analog machinery, technology became an inseparable part of daily activities. Besides the numerous advantages, the use of technology brings new problems. For instance, calibration of the machines is one of the important problems. The importance of the reasonable quality of measurements is recognized by researchers and developed specific methods for calibration. Also, numerical analysis is used as a shortcut in engineering applications. For example, partial differential equations without solutions can be approximated.

The other problem is the management of the collected information by machinery, such as sensors. Additionally, the collection of online activities is an important source of digitalized information. The stored digital data cannot be managed properly by humans, so interpretation of relevant information and automation requires machine learning algorithms.

To address all these issues within this book, a collection of eight chapters are presented by distinct researchers on the specified subject. The first three chapters are focused on calibration methods such as Multi-Objective Taguchi Technique in “Simultaneous Optimization of Burnishing Parameters Using Multi-Objective Taguchi Technique”, PID controller in “Improved Optimum PID Controller Tuning by Minimizing Settling Time and Overshoot”, and manually in “Optimization of Machining Parameters in Turning of Aisi 4340 Steel”. Chapter four is an analysis of supporting medical decisions by
image processing. The chapter is titled “A Novel Image Segmentation Technique for Medical Decision Support Systems: Osteoarthritis (OA) Knee Abnormality Detection from Hazy X-Ray Images Through Polygon Construction Based on Connected Line Segments”. Chapter five, “Remote Monitoring of Muscle Signals with Emg Sensor”. In the last chapter, digitization of muscle signals and broadcasting by IoT platforms. Chapter six compares balancing algorithms for imbalanced datasets. Their proposed method shows the best performance between the listed balancing algorithms. The chapter is titled “Improved Performance of Yeast Localization Prediction by Balancing with DBSCAN and Weighted Arithmetic Mean”. Chapter seven provides invaluable information on the numerical evaluation of experimentally gathered data. The chapter title is “Numerical Evaluation of Experimental Results for Buried Pipes in Geosynthetic Reinforced Sand”. Chapter eight is a simulation example of a mechanical engineering problem. This chapter presents the improvement of exhaust temperature as the title indicates “Use of Exhaust Valve Phase Shift Method for Accelerated Exhaust After-Treatment Heat-Up in Heavy-Duty Diesel Vehicles”. For the chapters, all responsibilities belong to the authors.

We are appreciated of authors’ contribution to this book and IKSAD publishing house. We hope this book informs and opens new doors to the reader as intended in Machinery and Digitization.

Assist. Prof. Merivan ŞAŞMAZ

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CHAPTER 1

SIMULTANEOUS OPTIMIZATION OF BURNISHING PARAMETERS USING MULTI-OBJECTIVE TAGUCHI TECHNIQUE

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INTRODUCTION

In the manufacturing industry, the surface quality of the workpiece is the most important parameter (Esme et al., 2013; Kulekci et al., 2014). The machining components are needed to be manufactured with good dimensional accuracy beside surface roughness to provide reliable performance and uninterrupted manufacturing (Chakraborty et al., 2017; Reddy et al., 2015; Hamamci et al., 2015). The burnishing process has been applied to manufactured components as the last process to decrease surface roughness, to rise corrosion resistance, wear resistance, surface hardness and fatigue life (Hamadache et al., 2014; Bourebia et al., 2019; Huang et al., 2015). Burnishing is a method using different burnishing devices such as ball or roller that are exposed to external forces on both a cylindrical and a flat workpiece surface.

Ball burnishing without removing chips from the surfaces of pre-treated materials is a surface finishing process used to reduce the surface roughness of the parts (Sönmez et al., 2016; El-Axir, 2000). Although most of the materials used in the experimental work are made of non-ferrous soft materials such as aluminum and brass, it is possible to use them in mild steel and hard metals as the capacity (El-Axir et al., 2008; El-Khabeery and El-Axir, 2001; Prevéy and Cammett, 2004; Başak et al., 2011).

Surface finishing operations can be easily done traditional machining methods of turning, milling, grinding, polishing, lapping or honing. Burnishing gives many advantages in comparison with traditional
machining methods. Unlike these methods, burnishing modifies surface roughness by plastic deformation of surface disorders without material loss. Burnishing is regarded as a straightforward, fast, effective, and cheap process with benefits like developing the mechanical properties of the machine parts. The primary burnishing parameters effecting the surface quality are listed as, ball size, burnishing force, speed, lubrication, number of passes, feed rate, workpiece and ball material, etc. (Sachin et al., 2019; Bourebia et al., 2017; Ovali and Akkurt, 2011; Stanković et al., 2012; Buldum and Cagan, 2018; Basak and Goktas, 2009).

Recently, surface finishing operations have attracted increased attention. When the studies in the literature are examined, mono-response optimization method is generally used for the optimization of the ball burnishing parameters on the surface roughness and microhardness.

In a search of the literature, many researchers concentrate on the influence of the burnishing parameters on surface roughness and hardness modeling and optimization with the use of mathematical models and statistical methods namely Artificial Neural Network (Stanković et al., 2012), Taguchi Technique (Buldum and Cagan, 2018), and Fuzzy logic (Basak and Goktas, 2009).

Taguchi Technique is a very effective method for solving optimization problems. This technique is an experimental and analytical approach that identifies the most influential factors on quality characteristics. The Taguchi technique provides a design opportunity that covers the
whole process with a little count of trials (Akkuş et al., 2017). Thus, great savings are achieved in terms of duration and price by decreasing the number of trials. In case of single output in manufacturing processes, the Taguchi Method based on Signal Noise S/N ratio is applied successfully (Bagci and Ozcelik, 2006). However, in case of multiple outputs, the traditional Taguchi method is not sufficient. In this case, techniques such as Multi-response (S/N) ratio-based Taguchi Method or Multi-criteria decision-making methods can be applied (Kahraman et al., 2018).

The optimization of multi-response performance characteristics is still an important research area. The literature represents that earlier researcher centered on the influence of the burnishing coping with surface roughness and hardness with the concentrate on optimization of the control factors.

In this study, optimization by multi-performance characteristics with multi-objective Taguchi technique has been utilized to maximize hardness and minimize roughness in the burnishing.

1. MATERIAL AND EXPERIMENTAL METHOD

1.1. Workpiece

AA 7075 aluminum alloy was chosen as the workpiece in the ball burnishing process. It is commonly used in aerospace and automotive industry owing to their low density (2.70 g/cm³) almost one third of that of steel (7.83 g/cm³), excellent strength, superior corrosion
resistance and formability (Davis, 1993; Vasudevan et al., 2012). The dimensions of the test sample are Ø30x100 mm.

1.2. Machines and Equipment

Stainless steel ball with a diameter of Ø18 mm and hardness of 60 HRc was used in the burnishing process. The ball burnishing tool technical drawing is displayed in Figure 1. The experiments were carried out on a Doosan brand Puma 240 model CNC lathe (Figure 2). The ball burnishing tool was fixed on the tool holder of the CNC lathe. During the ball burnishing process, there was no used coolant. In all experimental research, dry turning and ball burnishing processes were conducted. The overall workpiece was cleaned with alcohol before ball burnishing process. The ball was continuously cleaned to foreclose rigid particles from entering the touch surface between the burnishing tool and the workpiece.

![Figure 1: Technical Drawing of Ball Burnishing Tool](image)
Mitutoyo SJ201 model surface roughness tester was used for average surface roughness (Ra) measurement. The cut-off length was constant 0.3 mm for each roughness measurement. Surface roughness measurements were taken from different areas of each sample. Vickers hardness test was conducted using ZHVμ series Zwick microhardness tester under 50 N load for a duration of 10 seconds. To ensure the repeatability of the measurements were repeated 3 times for each workpiece. The experimental study was completed by following the procedure shown in Figure 3.
Figure 3: Flow Sequence of the Experimental Study

The most suitable orthogonal array L25 was selected to determine optimal burnishing parameters. Experimental results were evaluated using Minitab 17 statistical software. Selected control factors and their levels are shown in Table 1.
Table 1: Control Variables and Their Levels

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Factors</th>
<th>Unit</th>
<th>Levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Burnishing speed</td>
<td>m/min</td>
<td>30 50 70 90 110</td>
</tr>
<tr>
<td>B</td>
<td>Feed rate</td>
<td>mm/rev</td>
<td>0.05 0.15 0.25 0.35 0.45</td>
</tr>
<tr>
<td>C</td>
<td>Burnishing force</td>
<td>N</td>
<td>50 100 150 200 250</td>
</tr>
<tr>
<td>D</td>
<td>Number of passes</td>
<td>-</td>
<td>1 2 3 4 5</td>
</tr>
</tbody>
</table>

2. METHODOLOGY FOR MULTI OBJECTIVE TAGUCHI TECHNIQUE

Taguchi Technique has been used successfully in many areas to develop product quality and process performance. It has been used in the optimization of a single response. Generally, the quality of products is measured with more than one characteristic.

Analysis of multi-response outputs from an experiment needs to be done carefully. Response variables should not be analyzed individually and independently of the others, as possible relationships between responses will render univariate analyzes meaningless. In this case, it is pointless to obtain individual optimizers if it is desired to optimize multiple responses simultaneously. Where design variables depend on uncertain factors, the goal is to define the solution provided for all responses (Baynal, 2003).

Some modifications to the Taguchi Technique can be used for multi-response optimization. The objective of optimizing multiple quality characteristics is to detect the best factor levels that optimize all quality characteristics at the same time (Gaitonde et al., 2006). The
similarity to the Grey Relational Analysis (GRA), Vlse Kriterijumska Optimizaci I Kompromisno Resenje (VIKOR) and the Multi-Objective Taguchi Technique are used in multi-response optimization processes. MTT procedure is shown in Figure 4.

**Figure 4:** Multi-Objective Taguchi Technique Procedure

In this study, Taguchi Technique using a quality loss function was applied to determine simultaneously minimize surface roughness and maximize surface hardness. Multiple responses were transformed into a single response by simply adding normalized quality loss values (Muhammad, 2013; Mohamed et al., 2015; Kus et al., 2018). This method which was proposed by Tong et al. (1997) and Anthony (2001) has the following phases:
2.1. Compute the Quality Loss (Lij)

The quality loss value of each characteristic is determined using the quality loss function according to the purpose function of the quality characteristics.

$L_{ij}$ is calculated using the following formulas:

i) Equation (1) is utilized for larger the better response.

$$L_{ij} = \frac{1}{n_i} \sum_{k=1}^{n_i} \frac{1}{y_{ijk}^2}$$  \hspace{1cm} (1)

ii) Equation (2) is utilized for smaller the better response.

$$L_{ij} = \frac{1}{n_i} \sum_{k=1}^{n_i} y_{ijk}^2$$  \hspace{1cm} (2)

iii) Equations (3-5) are employed for nominal the best response.

$$L_{ij} = \left( \frac{\bar{y}^2}{S^2} \right)$$  \hspace{1cm} (3)

$$\bar{y} = \frac{1}{n_i} \sum_{k=1}^{n_i} y_{ijk}$$  \hspace{1cm} (4)

$$S^2 = \frac{1}{n_i - 1} \sum_{k=1}^{n_i} (y_{ijk} - \bar{y})^2$$  \hspace{1cm} (5)
where $n_i$: number of experiment repetition for the $i$th response, $y_{ijk}$: observed value for the $i$th response in the $k$th repetition of the $j$th experiment, $L_{ij}$: loss function of $j$th response in the $j$th experiment and $S^2$: variance.

### 2.2. Detect the Multi-Response Signal to Noise Ratio (MRSN)

$L_{ij}$ is calculated for each quality characteristic. Then, $TNQL_j$ and $MRSN$ for both quality characteristics were calculated using Equations (6-8).

$$C_{ij} = \frac{L_{ij}}{L_i^*}$$

$$L_i^* = \max \{L_{i1}, L_{i2}, ..., L_{ij}\}$$

where $C_{ij}$: normalized quality loss and $L_i^*$: maximum quality loss.

$$TNQL_j = \sum_{i=1}^{m} w_i C_{ij}$$

where $TNQL_j$: total normalized quality loss, $w_i$: weight factor for $i$th normalized response, $m$: number of response factors.

$$MRSN_j = -10 \log (TNQL_j)$$

### 2.3. Identify the Optimal Factor/Level Combinations

The influences of control factors on the quality characteristics can be analyzed with the assist of MRSN. These influences are described and
judged considering MRSN. A significant necessity when computing the optimal points is to describe the optimum levels of process parameters. They were identified by detecting distinct levels of the control factors, based upon the results from combinations generated by the orthogonal array. The levels of the control factors were established for quality characteristics.

2.4. Analysis of Variance (ANOVA)

In this stage, ANOVA was utilized to analyze the effects of process parameters on quality characteristics. The aim of the analysis is to search which control parameters considerably effect the performance characteristics. It was also performed at 5% significance and 95% confidence level.

2.5. Confirmation Experiments

Prior to the optimal level of the burnishing parameters is preferred, the last step of MTT is to estimate and confirm the development of the performance characteristics by using the optimal combination. The predicted MRSN for the optimum level of the burnishing parameters was computed by Equation (9).

\[ \eta_{opt} = \eta_{bn} + \sum_{i=1}^{p} (\eta_{mi} - \eta_{bn}) \]  (9)
where $\eta_{opt}$: estimated value of MRSN, $\eta_m$: total mean of MRSN, $\eta_{mi}$: mean of MRSN, and $p$: number of major parameters that influence the quality characteristic.

3. RESULTS AND DISCUSSION

In this survey, the smaller-the-better and larger-the-better quality characteristics were chosen for roughness and hardness, respectively. The experimental results were represented in Table 2. $L_{ij}$ values of each response were obtained using Equations (1) and (2). $C_{ij}$ values were calculated using Equation (6). $TNQL_j$ values have been established using Equation (7). A weight coefficient is assigned for each response. In this case, the weight coefficient of each response is significant. The weight coefficient was determined for each response so that the total weight coefficient was 1. Weighting factors for surface roughness and hardness were selected as $w_1=0.70$, $w_2=0.30$, respectively. Esme (2010) optimized the ball burnishing parameters using Taguchi-based Gray relationship analysis. The weights of the quality characteristics were determined as 0.67 for roughness and 0.33 for microhardness, respectively. The weights used for the quality characteristics in this study were used in accordance with the literature.
<table>
<thead>
<tr>
<th>Trial No</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>Ra (µm)</th>
<th>Hardness (HV)</th>
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</table>

*MRSN*<sub>ji</sub> ratio values were computed by using Equation (8). \( L_{ij} \), \( C_{ij} \), \( TNQL_{ij} \) and *MRSN*<sub>ji</sub> ratio values obtained from Equations (1), (2) and (6-8) were summarized in Table 3. The average of MRSN ratio values for each level of the burnishing parameters was computed and results were given in Table 4.
Table 3: \( L_{ij}, C_{ij}, TNQL_j \) and \( MRSN_j \) Ratio Values

<table>
<thead>
<tr>
<th>Trial Number</th>
<th>( L_{ij} ) (dB)</th>
<th>( C_{ij} )</th>
<th>( TNQL_j )</th>
<th>( MRSN_j ) ratio (dB)</th>
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<td>0.3364</td>
<td>0.000025</td>
<td>0.3432</td>
<td>0.680625</td>
</tr>
<tr>
<td>22</td>
<td>0.8836</td>
<td>0.000030</td>
<td>0.9015</td>
<td>0.804141</td>
</tr>
<tr>
<td>23</td>
<td>0.4225</td>
<td>0.000029</td>
<td>0.4311</td>
<td>0.795471</td>
</tr>
<tr>
<td>24</td>
<td>0.4624</td>
<td>0.000029</td>
<td>0.4718</td>
<td>0.778547</td>
</tr>
<tr>
<td>25</td>
<td>0.9801</td>
<td>0.000026</td>
<td>1.0000</td>
<td>0.715976</td>
</tr>
</tbody>
</table>

The overall average \( MRSN \) ratio value: 2.633

The optimal levels of the ball burnishing parameters were obtained as 70 m/min burnishing speed, 0.05 mm/rev feed rate, 100 N burnishing force, 4 number of passes for multiple quality characteristics. Likewise, the optimal combination of burnishing parameters was established as \( A_3B_1C_2D_4 \) from Table 4.
Table 4: Response Table For MRSN

<table>
<thead>
<tr>
<th>Factors</th>
<th>Level 1</th>
<th>Level 2</th>
<th>Level 3</th>
<th>Level 4</th>
<th>Level 5</th>
<th>Max-Min</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>2.698</td>
<td>2.493</td>
<td>3.765*</td>
<td>2.275</td>
<td>1.933</td>
<td>1.832</td>
<td>2</td>
</tr>
<tr>
<td>B</td>
<td>3.760*</td>
<td>2.456</td>
<td>2.737</td>
<td>2.854</td>
<td>1.355</td>
<td>2.405</td>
<td>1</td>
</tr>
<tr>
<td>C</td>
<td>2.340</td>
<td>3.047*</td>
<td>2.713</td>
<td>2.314</td>
<td>2.749</td>
<td>0.409</td>
<td>4</td>
</tr>
<tr>
<td>D</td>
<td>2.738</td>
<td>2.848</td>
<td>2.857</td>
<td>2.957*</td>
<td>1.763</td>
<td>1.195</td>
<td>3</td>
</tr>
</tbody>
</table>

The quality characteristics are conducted to define the most significant factor in control factors by ANOVA. This analysis was performed for a confidence level of 95%. ANOVA results of MRSN are given in Table 5. As seen Table 5, the percent contribution of the burnishing parameters on the multi-performance characteristics was acquired to be feed rate (45.05%), burnishing speed (28.92%), number of passes (14.59%) and burnishing force (5.70%). The results demonstrate that the feed rate was found to be a dominant factor among burnishing parameters.

Table 5: Results of ANOVA

<table>
<thead>
<tr>
<th>Variance Source</th>
<th>Degree of freedom (DF)</th>
<th>Sum of squares (SS)</th>
<th>Mean square (MS)</th>
<th>F-Value</th>
<th>P-Value</th>
<th>Contribution (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>4</td>
<td>9.615</td>
<td>2.4038</td>
<td>10.07</td>
<td>0.003</td>
<td>28.92</td>
</tr>
<tr>
<td>B</td>
<td>4</td>
<td>14.975</td>
<td>3.7438</td>
<td>15.69</td>
<td>0.001</td>
<td>45.05</td>
</tr>
<tr>
<td>C</td>
<td>4</td>
<td>1.894</td>
<td>0.4736</td>
<td>1.98</td>
<td>0.190</td>
<td>5.70</td>
</tr>
<tr>
<td>D</td>
<td>4</td>
<td>4.851</td>
<td>1.2127</td>
<td>5.08</td>
<td>0.025</td>
<td>14.59</td>
</tr>
<tr>
<td>Error</td>
<td>8</td>
<td>1.909</td>
<td>0.2387</td>
<td></td>
<td></td>
<td>5.74</td>
</tr>
<tr>
<td>Total</td>
<td>24</td>
<td>33.245</td>
<td></td>
<td></td>
<td></td>
<td>100</td>
</tr>
</tbody>
</table>
Verification test was conducted to estimate and verify the enhancement of the quality characteristics using the optimum burnishing parameter level (A$_3$B$_1$C$_2$D$_4$) of the control factors. The estimated MRSN ratio for the optimal level of the process parameters was calculated using Equation (9). Experimental and predicted results obtained with the MTT was shown in Table 6. When the predicted value of MRSN (5.627dB) was compared with the experimental value of MRSN (5.790 dB) in the optimal level of burnishing parameters a relatively good agreement was found. The percentage improvement in MRSN with the multi responses is 55.56%. The value of roughness and hardness at the optimum levels of the process parameters are 0.29 µm and 195.8 HV, respectively against the random parameters setting of 0.55 µm and 178 HV. Hence, significant performance improvement in both surface roughness and hardness has been obtained. Based on the result of the confirmation test, the surface roughness is decreased as 1.90 times and surface hardness is increased 0.91 times. Therefore, it can be said that the multiple performance criteria are importantly enhanced in the ball burnishing of AA 7075 aluminum alloy together by using the MTT.
<table>
<thead>
<tr>
<th>Level</th>
<th>Random burnishing parameters</th>
<th>Optimal burnishing parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Prediction</td>
<td>Experiment</td>
</tr>
<tr>
<td></td>
<td>A₃B₃C₅D₂</td>
<td>A₃B₁C₂D₄</td>
</tr>
<tr>
<td>Ra (µm)</td>
<td>0.55</td>
<td>-</td>
</tr>
<tr>
<td>Hardness (HV)</td>
<td>178</td>
<td>-</td>
</tr>
<tr>
<td>MRSN ratio (dB)</td>
<td>3.722</td>
<td>5.627</td>
</tr>
</tbody>
</table>

Improvement in MRSN ratio = 2.068 dB.

The percentage improvement in MRSN = 55.56%

It is very important to increase the surface quality of the materials that are chipped by the machining method. Grinding, honing, high precision machining and ball burnishing process are applied to obtain a quality surface. When the studies in the literature are examined, ball burnishing is the most suitable method for reducing the roughness of the workpiece and increasing the hardness (Koçak, 2020).

Esme et al. (2013) applied the burnishing process to AA 7075 aluminum alloy material and obtained the lowest roughness value as 0.82 µm. Basak and Sonmez (2017) acquired the minimum roughness value of 0.423 µm and the maximum hardness value of 200.67 HB by applying ball burnishing process to AA 6061. Kurkute and Chavan (2018) optimized the surface roughness and microhardness values using RSM-based desirability function analysis. The optimized values were obtained as the roughness value of 0.524 µm and the microhardness value of 125.02 HV, respectively. Cagan and Buldum (2018) performed the ball burnishing process to 7075 aluminum alloy.
The lowest roughness value obtained under the optimal condition was determined as 0.67 μm. The results obtained as a result of this study were found to be similar when compared with the literature.

CONCLUSION

This study presented a new approach of the Taguchi technique to optimize performance parameters of the burnishing process on AA 7075 aluminum alloy. Multiple quality characteristics were considered simultaneously using MTT. The main results were as follows:

- The optimum burnishing conditions were acquired as 70 m/min burnishing speed, 0.05 mm/rev feed rate, 100N burnishing force and 4 number of passes by using MTT.
- The percent contribution of the burnishing parameters on multi-response was obtained to be feed rate (45.05 %), burnishing speed (28.92 %), number of passes (14.59 %) and burnishing force (5.70 %) with ANOVA. The most effective control factor is feed rate.
- The results of the confirmation test shown that the MRSN ratio was an increase of 2.068 dB compared to the optimal performance parameters of the random parameters. The decrease of surface roughness was calculated to be 1.90 times and the increase of surface hardness was calculated to be 0.91 times.
- As a result, this method can be effectively employed for multiple quality characteristic optimizations of the complicated manufacturing problems.
In the future study, the distinct relative weights appoint to multi-response can be studied and optimal process conditions can be determined. Multi-criteria decision-making methods can be applied in solving multi-response problems.
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CHAPTER 2

IMPROVED OPTIMUM PID CONTROLLER TUNING BY MINIMIZING SETTLING TIME AND OVERSHOOT

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INTRODUCTION

PID controllers are widely used in industrial control systems thanks to their simple structure, easy design, robust performance, low cost, ease of application and wide application range. An adjusted proportional gain ($k_p$), an integral gain ($k_i$) and a differential gain ($k_d$) form the basis of the PID controller to obtain the optimal response of the system to be controlled. The main challenge in the control process is to minimize the difference between a set point and the measured process variable in as little time as possible. However, finding the optimal value for $k_p$ becomes difficult when the control process complex or nonlinear behavior occurs. Several methods have been proposed to adjust the PID controller gains. The oldest and simplest method is the Ziegler and Nichols method (Ziegler and Nichols 1942). However, in this method, high settlement time and overshoot are observed in closed loop responses. Therefore, every response needs to be refined. In another study, a method was proposed to select the proportional gain value (Cohen and Coon 1953). Other common methods suggested are as follows: Astrom and Haggland method (Astrom and Hagglund 2001), optimization method (Manoj and Chidambaram 2001; Visioli 2001), gain and phase margin method (Paor and Malley 1989; Venkatashankar and Chidambaram 1994; Ho and Xu 1998; Wang and Cai 2002), direct synthesis method (Clement and Chidambaram 1997), weighted geometric center method (Turan et al. 2019). Besides, research of new control methods for calculating each optimal gain value of PID controller is seen in many studies (Ali et al. 2014; Mittalet al. 2013; Fereidouni et al. 2015; Wu et al. 2016;
In this study, PID controller design is proposed based on setting the optimal proportional gain according to the desired performance from the system (settling time, overshoot). The method is based on the determination of the $k_p$ value that will minimize the error rates of the desired settling time and overshoot values in this loop by creating a loop in the stable area, and the calculation of the $k_i$ and $k_d$ values according to this $k_p$ value. This simple adjustment method has some advantages over existing adjustment methods. Solution processes are simple since there is no need for complex mathematical formulations. Better performance responses were obtained in three different models compared to other methods. Better performance responses were obtained compared to other compared methods.

This study has 4 section. In section 2, the methodology of the proposed method has been presented, and then, in Section 3, simulation studies have been conducted on different examples. In the last section, the results have been given.

1. METHODOLOGY

This method has been applied on three different system models. Figure 1 shows the block diagram of the unit feedback control system.
C(s) is the transfer function of the PID controller and it is given in Eq. (1). G(s) is the transfer function of the system Eq. (2). r, e and y define input, error and output, respectively.

\[
C(s) = k_p + \frac{k_i}{s} + k_d \tag{1}
\]

\[
G(s) = \frac{G_N(s)}{G_M(s)} \tag{2}
\]

\(G_N(s)\) and \(G_D(s)\) show the numerator and denominator of G(s), respectively. If Eq. (1) is arranged, the general controller equation is obtained Eq. (3).

\[
C(s) = \frac{(k_ds^2 + k_ps + k_i)}{s} \tag{3}
\]

Accordingly, the closed loop system T(s) is obtained in Eq. (4).

\[
T(s) = \frac{C(s)G(s)}{1+(C(s)G(s))} \tag{4}
\]

If Eq. (2) and Eq. (3) are replaced in Eq. (4), Eq. (5) is obtained.
Here, $T_D(s)$ is checked at the characteristic equation of the system and its degree is determined. Then, settling time ($t_s$) and overshoot ($M_p$) value are determined according to the performance required from the system and damping ratio $\zeta$ is calculated with Eq. (6).

$$\zeta = \frac{-\log(M_p)}{\sqrt{\pi^2 + \log(M_p)^2}}$$

(6)

The natural frequency of the system is obtained by Eq. (7).

$$\omega_n = \frac{4}{\zeta t_s}$$

(7)

The target polynomial of the closed loop system is given in Eq. (8).

$$\Delta(s) = s^2 + 2\zeta \omega_n s + \omega_n^2$$

(8)

Here, the degree of $\Delta(s)$ is 2. Therefore, a residue polynomial $R(s)$ is needed for those with system degree above 1. It should also contain as many uncertain variables as the degree difference ($m$) between $T_D(s)$ and $\Delta(s)$.
The fact that $a_1, a_2, a_3, \ldots, a_n \in \mathbb{R}$ here keeps the system away from complexity and makes it include all solutions. The problem here is that the coefficients of the product of $\Delta(s)$ and $R(s)$ in a closed loop system must be equal to the coefficients of the characteristic equation of the system Eq. (10).

$$R(s) = \begin{cases} 
    s + a, & m = 1 \\
    s^2 + a_1s + a_2, & m = 2 \\
    s^3 + a_1s^2 + a_2s + a_3, & m = 3 \\
    s^n + a_1s^{n-1} + a_2s^{n-2} + \ldots + a_n s^{n-m}, & m = n 
\end{cases}$$ (9)

When looking in Eq. (10) obtained for systems with degree more than 1, it will be seen that the number of variables is 1 more than the number of meaningful equations. Therefore, by subtracting $k_p$ from variables $(k_p, k_i, k_d, a_1, a_2, \ldots, a_N)$, the number of variables is reduced by 1 and equalized to the number of equations. By solving Eq. (10) again, all variables are solved with terms containing $k_p$ and it is concluded that there are many multiple choice solutions.

Given the stability state, $\Delta(s)$ was chosen to be stable. The remaining polynomial is the $R(s)$ polynomial whose stability must be checked. Therefore, if the variables $(a_1, a_2, \ldots, a_N)$ in $R(s)$ are positive, it is sufficient for stability. While determining these values, positive values should be chosen.
After determining the variables positive, values are assigned to $k_p$ in a certain interval and in an incremental cycle, variables ($k_p$, $k_i$, $k_d$, $a_1$, $a_2$... $a_N$) $t_s$ and $M_p$ values are determined in the responses of the system. The aim is to obtain a value as close as possible to the expected (desired) value of $t_s$ and $M_p$. Therefore, $t_s$ and $M_p$ need to be normalized. For this, the error rates for $M_p$ and $t_s$ are assigned to variables $e_1$ and $e_2$, respectively.

$$e_1 = \frac{M_p-M_{p\text{abs}}}{M_p} \quad (11)$$

$$e_2 = \frac{t_s-t_{s\text{ans}}}{t_s} \quad (12)$$

Eq. (11) and Eq. (12) are combined to obtain Eq. (13) if it is desired to be represented in a single error.

$$\text{err} = xe_1 + ye_2 \quad (13)$$

Here, $x$, $y$ is the coefficient affecting the total error and $x$ and $y$ values are chosen according to the importance expected from the system and $x + y = 1$. The obtained $\text{err}$ value is also added to the loop and determined according to $k_p$. As a result, the PID controller parameters $k_p$, $k_i$ and $k_d$ are obtained according to the value $\text{err}_{\text{min}}$ determined at the end of the cycle performed.

Figure 2 shows the algorithm of the proposed PID control method.
Fig. 2: The Algorithm of the PID Control Method
2. SIMULATION STUDIES

The application of the controller designed on three different models in MATLAB 18b has been made to show how effective the proposed method. $M_p$, $t_s$, and rise time ($t_r$) were used as performance criteria in simulations.

**Example 1.** Consider the 2nd order stable model given in Eq. (14).

$$G(s) = \frac{1}{0.9941s^2 + 11s + 30}$$  \hspace{1cm} (14)

It has been studied by (Deniz et al., 2015). Here, the range value $k_p=[-6.6, 300]$ was chosen for $k_p$ in 0.01 increments. The reason why the first value does not start from zero is the result of a $<0$ in the $R(s)$ polynomial for $k_p > -6.6$ values, therefore the system has been showed unstable behavior.

A loop was created by selecting the total error value $Err=0.5e_1 + 0.5e_2$.

The PID controller parameters where the $err_{\text{min}}$ value is obtained in the loop performed are given in Table 1. Fig. 3 is given the unit step responses in closed loop with PID. In addition, the bode plots of the PID controller system is shown in Fig. 4. In the unit step response of the proposed PID controller system, a better $t_s$ has been obtained, although the difference is small, as well as a much better $M_p$. We can say that the proposed PID controller performs better. Performance criteria of the controller proposed in this study and by Deniz et al., (2015) are given in Table 1.
The root locus graph for the system with the PID controller is given in Fig. 5. The characteristic equation for all the closed loop is its roots in the left half of the ‘s’ plane. So the system is stable.

![Plot](image.png)

**Fig. 3:** Step Responses for Example 1
Fig. 4: Bode Plot of System with PID for Example 1

Fig. 5: Root Locus Graph of System with PID for Example 1
Example 2. Consider the 3rd order stable and moderate oscillation hydraulic seedling collection system model given in Eq. (15).

\[
G(s) = \frac{208.75}{s^3 + 14.31s^2 + 447.53s + 208.75}
\]  

(15)

The proposed method is compared with conventional PID design by Jin et al. (2000). Here, the range value \( k_p = [0, 100] \) was chosen for \( k_p \) with an increment of 0.01. The reason why the first value starts from zero is that the system behaves unstable as it creates the result \( a < 0 \) in the \( R(s) \) polynomial for \( k_p < 0 \) values. The total error value is \( \text{Err} = 0.5e_1 + 0.5e_2 \).

The gain parameters from which the \( \text{err}_{\text{min}} \) value is obtained in the cycle performed are given in Table 1. In the step response, 0.02 m was chosen as the input signal and the simulation curve was obtained as shown in Fig. 6. The bode plots of the PID controller system is shown in Fig. 7. The system has good dynamic performance, fast response and low steady-state error. It is clear that the proposed PID controller has a better performance. When we look at the performance criteria obtained, it is seen that better \( t_s, M_p \) and \( t_r \) (Table 1).

The root locus graph for the system with the PID controller is given in Fig. 8. The characteristic equation for all the closed loop is its roots in the left half of the ‘s’ plane. So the system is stable.
Fig. 6: Step Responses for Example 2

Fig. 7: Bode Plot of System with PID for Example 2
Example 3. Consider the 3rd order unstable model given in Eq. (16).

\[ G(s) = \frac{1}{s^3 + 4s^2 + s - 6} \]  \hspace{1cm} (16)

It has been studied by [19]. Here, the range value \( k_p = [10, 100] \) was chosen for \( k_p \) with an increment of 0.1. The reason why the first value does not start from zero is that the system behaves unstable as the result \( a < 0 \) in the \( R(s) \) polynomial for \( k_p < 9.9 \) values. The total error rate was selected as \( \text{Err} = 0.5e_1 + 0.5e_2 \).

The gain parameters of PID controller from which the \( \text{err}_{\text{min}} \) value is obtained in the cycle performed are given in Table 1. The unit step responses in closed loop by applying PID and obtained PID control proposed by Patel and Janardhanan (2020) to the system are given in

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**Fig. 8:** Root Locus Graph of System with PID for Example 2
Fig. 9. In addition, the bode plot of the proposed PID controller system is shown in Fig. 10. It has been observed that the designed PID controller system results in better results in step response of all performance criteria including $t_s$, $M_p$ and $t_r$. Therefore, we can easily say that the designed PID controller has a better performance.

The root locus graph for the system with the PID controller is given in Fig. 11. The characteristic equation for all the closed loop is its roots in the left half of the ‘s’ plane. So the system is stable.

![Graph showing step responses for Example 3](image_url)

**Fig. 9**: Step Responses for Example 3
Fig. 10: Bode Plot of System with PID for Example 3

Fig. 11: Root Locus Graph of System with PID for Example 3
Table 1. Controllers Parameters and Values of The Performance Criteria for Examples

<table>
<thead>
<tr>
<th>PID controller gain</th>
<th>Values of the performance criteria</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$k_p$</td>
</tr>
<tr>
<td>Example 1. $G(s) = \frac{1}{0.9941s^2+11s+30}$</td>
<td></td>
</tr>
<tr>
<td>Proposed</td>
<td>30.4</td>
</tr>
<tr>
<td>(Deniz et al., 2015)</td>
<td>268.23</td>
</tr>
<tr>
<td>Example 2. $G(s) = \frac{208.75}{s^3+14.31s^2+447.53s+208.75}$</td>
<td></td>
</tr>
<tr>
<td>Proposed</td>
<td>19.2</td>
</tr>
<tr>
<td>(Jin et al., 2000)</td>
<td>4</td>
</tr>
<tr>
<td>Example 3. $G(s) = \frac{1}{s^3+4s^2+s-6}$</td>
<td></td>
</tr>
<tr>
<td>Proposed</td>
<td>62.2</td>
</tr>
<tr>
<td>(Patel and Janardhanan 2020)</td>
<td>31</td>
</tr>
</tbody>
</table>
CONCLUSION

This paper presents a simple design method for setting the parameters of the PID controller. In the proposed method, the other parameters of the PID controller are determined according to the desired performance ($t_s$, $M_p$) of the system, in response to the adjustment of the optimum proportion gain ($k_p$) in a stable loop so that the error rate of $t_s$ and $M_p$ are minimized. The performance of the controller designed with the proposed method has been evaluated on three different transfer functions. It is seen that this method, which has advantages such as not destroying parameters and not including complex mathematical formulation, provides better performance than other methods. In addition, the results obtained show that the method can be easily applied to different systems.
REFERENCES


CHAPTER 3

OPTIMIZATION OF MACHINING PARAMETERS IN TURNING OF AISI 4340 STEEL

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INTRODUCTION

The annealed AISI steel has good ductility which allows for substantial formability. However, the hardened AISI 4340 steel has high strength, good toughness, good abrasion, wear, shock, and impact resistance thanks to the carbon percentage in its composition. It is alloyed steel having chromium, nickel, and molybdenum in its content. The 4340 material is usually used as hardened and tempered steel with high tensile strength up to 1080 Mpa. It is also possible to perform surface hardening using induction or flame. AISI 4340 steel is widely used in the aerospace industry for structural components where the main structural requirements are strength and toughness (Atlas Specialty Metals, 2005; Fakir et al., 2018)

The main purpose of turning, which is one of the most widely used methods in the field of machining, is to obtain high size and complete product quality at the lowest cost. Cutting parameters have an important effect on obtaining the desired product quality. It is possible to improve the tool wear and surface roughness value by selecting these parameters according to the working conditions. For this purpose, it is seen that studies investigating the effects of different cutting parameters on surface roughness and cutting forces have been conducted (Işık and Çakır, 2001; Özdemir, 2019). In one of these studies, Khara et al. investigated the effect of AISI 4340 alloy steel on surface roughness, cutting forces, and temperature depending on cutting speed (V), feed rate (f), depth of cut (a), and tool radius (R) using uncoated carbide tool in dry cutting conditions. The
experimental design was made using analysis of variance (ANOVA), regression, and Gray Relational Analysis (GRA). It is stated that the cutting parameters have a remarkable effect on the response variables (Khara et al. 2019). The cutting inserts can be either coated or uncoated for performing the machining process. Sahoo et al; experimentally examined the flank wear, surface roughness, chip shape, and cutting force based on the cutting parameters \(V, f, \) and \(a\) during finish turning of AISI 4340 steel using coated and multi-layered TiN and ZrCN and carbide coated inserts at high cutting speeds. They used the regression model and ANOVA in the experimental study. It has been determined that the surface roughness gives better results when using a multi-layered carbide insert (Sahoo, 2012). Suresh et al., have used Taguchi's experimental technique and regression model. They carried out a study on reducing cutting forces and improving surface quality. As a result of this study, it was stated that a high feed rate should be selected to minimize the cutting force. For the lowest surface roughness value, it was determined that low feed rate and high cutting speed values are desirable (Suresh et al., 2012a). Various analyses and methods are also used while performing these studies. Thanks to these tools, the test results can be interpreted more accurately. In a study by Gupta et al., the Response Surface Method (RSM) and mathematical models were used to predict the surface roughness in turning of AISI 4340 alloy steel. According to the results, the most important parameter affecting the surface roughness value is the \(f\), followed by \(V\) (Gupta, 2014). In another study using the RSM method, Suresh et al., presented the effect of
cutting parameters on the cutting force, surface roughness, and tool wear in turning of AISI 4340 material. They planned the experimental study as a full factorial design. According to the results of parametric analysis; It has been determined that with low \( f \), low \( a \), low machining time, and high cutting speeds minimum cutting force and surface roughness can be achieved (Suresh et al. 2012b). Using the analysis of variance technique, More et al. experimentally investigated the effects of \( V \) and \( f \) on tool wear (tool life), surface roughness, and cutting forces using CBN-TiN coated carbide inserts. As a result of the experiments, it was determined that the surface roughness value was less than 1.3 \( \mu \text{m} \) (More et al., 2006). Sudhansu et al. investigated surface roughness, flank wear, and chip morphology during dry hard turning of AISI 4340 steel (49 HRC) using CVD (TiN/TiCN/Al2O3/TiN) coated carbide tool. The cutting speed \( V \), feed rate \( f \), and depth of cut \( a \) were selected as cutting parameters. Three-level factorial experimental designs with Taguchi’s L9 orthogonal array and statistical analysis of variance were used to interpret the results of these experiments. The results showed that surface roughness and flank wear were significantly affected by \( f \) and \( V \) (Sudhansu et al., 2018). In another study, the effects of \( R \), \( V \), \( f \), and \( a \) parameters on surface roughness were investigated in turning hardened AISI 4340 steel. Taguchi’s technique was used in the experiment and the multiple regression method was used to optimize the machining parameter for minimum surface roughness. The results indicated that the nose radius \( R \) is the most influential parameter on the surface roughness in hard turning (Silva et al., 2020). In another
study conducted by Agrawal et al; The effects of cutting parameters (f, a, and V) on the surface roughness were experimentally investigated in turning AISI 4340 steel (with a hardness of 69 HRC) on a CNC lathe under dry cutting conditions. Regression (multiple regression, random forest, and scatter regression) models were used in the study. According to the results, the random forest regression model gave good results in the estimation of the surface roughness (Agrawal et al., 2015). Karabatak and Kara investigated the performance of cutting parameters (V, f, and a) and their effects on surface roughness in hard turning of AISI D2 material using Taguchi L9 experimental design and ANOVA (Karabatak and Kara, 2016). In another study, machining parameters such as V, f, a, and rake angle were optimized for minimum surface roughness on AISI 4340 steel under cryogenic conditions. The experiment was planned using Taguchi’s L9 array. An orthogonal array (L9), signal-to-noise (S/N) ratio was used to examine the surface roughness. According to the results of the experiment, it was determined that the most effective factors on the surface roughness were V and a (Khare and Agarwal, 2017). Patole et al. focused on the optimization of process parameters using AISI 4340 material and nanofluid. In the experiment, five f values, three a values, two V values, and R parameters were used. The surface roughness of the machined surface was measured using a surface measuring tester. Taguchi methodology was used to optimize the process parameters. The results of the experiment were analyzed using the ANOVA. From these analyses, it was stated that f plays an important role in obtaining lower surface roughness (Patole and Kulkarni, 2018). In Yılmaz and
Güllü study’s, the results were analyzed with the Taguchi L9 orthogonal array experimental design and ANOVA. It was determined that the most effective factor affecting the surface roughness was \( f \) (Yılmaz and Güllü, 2020). Özbek investigated the effect of cutting parameters \((a, f, \text{ and } V)\) on surface roughness and cutting tool performance in turning of AISI H11 steel. In this study, different experiments were carried out to determine the best cutting parameters (Özbek, 2020). Akkuş carried out a study to evaluate the effect of cutting parameters on surface roughness in turning AISI 1040 steel. For his study, the Design Expert and Matlab program, RSM, Box-Behnken design, ANOVA analysis, and artificial neural network (ANN) were used to analyze the results. According to the findings of the analysis, it was stated that the RSM has approximately 90% accuracy to predict the results (Akkuş, 2020). In another study, a combination of Artificial Neural Network (ANN) and Genetic Algorithm (GA) methodology was proposed to find the best machining process parameters in turning AISI 4340 material (Santhosh et al. 2021). Yaşar et al. compared the machinability of precipitation-hardened 17-4 PH and 15-5 PH stainless steel materials. For this comparison, the optimum cutting parameters were determined by investigating the effects of input parameters on cutting forces and surface roughness (Yaşar et al., 2020). CNC lathes are also widely used in the manufacturing sector and have been the subject of many studies. In one of these studies, Tekaslan et al. carried out a study on the effect of cutting parameters on surface roughness in turning AISI 304 austenitic stainless steel material on a CNC lathe. They
emphasized that increasing the $V$ improves the surface roughness. However, contrary to this phenomenon, it was stated that the surface roughness deteriorated as a result of increasing the $f$ (Tekaslan et al., 2008). In another study conducted on CNC lathe by Yaka et al., the effect of cutting parameters on surface roughness was investigated in turning 46 HRC hard AISI 1040 steel under dry cutting conditions. Taguchi L9 experimental design was applied and multiple regression and Minitab14 program were used to analyze these experimental results. The feed rate was determined as the most effective parameter on the response (Yaka et al., 2016). Memiş and Turgut conducted a study on the effects of cutting parameters ($a$, $f$, and $V$) on the surface roughness and cutting forces in turning of AISI 2205 duplex stainless steel. As a result of the experiments, it was stated that the best surface roughness values were obtained at the lowest feed rate value (Memiş and Turgut, 2020).

In this study, the effect cutting parameters (different $R$, $f$, $a$, and constant $V$) was investigated on the cutting force and surface roughness in dry turning of AISI 4340 steel. The experimental design was made according to Taguchi L9 orthogonal array. The results of the experimental study were analyzed using ANOVA analysis.
MATERIALS AND METHOD

In dry of turning AISI 4340 material on CNC lathe a fixed cutting speed: \( V \) (150 m/min), three different nose radii: \( R \) (0.4, 0.8, and 1.2 mm), three different feed rates: \( f \) (0.03, 0.06, and 0.09 mm/rev), and three different depths of cut: \( a \) (0.05, 0.1, and 0.15 mm) were used as cutting parameters. An experimental study was carried out to examine the effects of cutting parameters on radial force (Fx), feed force (Fz), and surface roughness (Rz). Turning experiments were carried out on the GOODWAY GS-260Y brand CNC lathe. The material to be turned is Ø70 mm in diameter and the machining length is 20 mm. Mahr MarSurf PS10 brand and model surface roughness measuring device was used for average surface roughness measurements (measurement length \( R_z \) 9.5 \( \mu \)m lt: 4.8mm). KISTLER TYPE 9129 AA brand and model dynamometer measuring device was used to measure cutting forces. In the experimental study, the experiments were repeated three times and the arithmetic average was taken. Figure 1 shows the experimental setup used in the study.
Figure 1: Experimental setup

The experimental set was created using the Taguchi L9 orthogonal array. Table 1 shows the cutting parameters ($R$, $f$, and $a$) and levels.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Symbol</th>
<th>Unit</th>
<th>Level 1</th>
<th>Level 2</th>
<th>Level 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tool nose radius</td>
<td>$R$</td>
<td>mm</td>
<td>0.4</td>
<td>0.8</td>
<td>1.2</td>
</tr>
<tr>
<td>feed rate</td>
<td>$f$</td>
<td>mm/rev</td>
<td>0.03</td>
<td>0.06</td>
<td>0.09</td>
</tr>
<tr>
<td>Depth of cut</td>
<td>$a$</td>
<td>mm</td>
<td>0.05</td>
<td>0.1</td>
<td>0.15</td>
</tr>
</tbody>
</table>

AKKO TTJNL 2525 M16 brand tool holder was used in the turning process. VCMT 160404-SM, VCMT 160408-SM, and VCMT 160412-SM were preferred as cutters. The cutting tool geometries for the VCMT 160412-SM insert are given in Figure 2. Two other cutting inserts have the same geometry except for tool nose radius (0.4 and 0.8 mm).
TAGUCHI METHOD

The Taguchi method is an experimental design technique that greatly reduces the number of experiments by using orthogonal networks and also attempts to minimize the influence of uncontrolled factors. The biggest advantages of the Taguchi method; It shortens the number and duration of experiments, reduces the cost, reveals the effective factors, and the optimum cutting parameters in a shorter time. In this method, S/N ratios can be calculated according to the nominal best, the smallest is the best and the largest is the best method (Özdemir et al., 2020; Taguchi et al., 1989, Taguchi and Konishi, 1987). In this study, Equation 1 is used because the minimum surface roughness and cutting force values are desired.
\[
\frac{s}{N} = -10 \cdot \log \left( \frac{1}{n} \cdot \sum_{i=1}^{n} Y_i^2 \right) 
\]  

(1)

**NUMERICAL ANALYSIS AND EVALUATION**

The effects of \( R, f, \) and \( a \) factors on the \( F_x, F_z, \) and \( R_z \) values were investigated experimentally. The Taguchi L9 orthogonal array and the experimental results obtained are shown in Table 2. Minitab 16 software and ANOVA were used to analyze the effects of cutting parameters. When Table 2 is examined, the levels and values of the cutting parameters for the lowest \( F_x \) (20.42 N) and \( F_z \) (30.17 N) were determined as \( R_1-f_1-a_1 \), and \( R_2-f_3-a_1 \), respectively. The parameters and levels for minimum \( R_z \) (1.64 \( \mu \)m) value were obtained as \( R_3-f_1-a_3 \).

**Table 2.** Taguchi L9 array and obtained results

<table>
<thead>
<tr>
<th>No</th>
<th>Cutting Parameters</th>
<th>Cutting forces</th>
<th>Surface roughness</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>R (mm) f (mm/rev) a (mm)</td>
<td>Fx (N)</td>
<td>Fz (N)</td>
</tr>
<tr>
<td>1</td>
<td>0.4 0.03 0.05</td>
<td>20.42</td>
<td>35.78</td>
</tr>
<tr>
<td>2</td>
<td>0.4 0.06 0.1</td>
<td>34.71</td>
<td>49.27</td>
</tr>
<tr>
<td>3</td>
<td>0.4 0.09 0.15</td>
<td>41.50</td>
<td>62.71</td>
</tr>
<tr>
<td>4</td>
<td>0.8 0.03 0.1</td>
<td>40.48</td>
<td>42.50</td>
</tr>
<tr>
<td>5</td>
<td>0.8 0.06 0.15</td>
<td>51.18</td>
<td>59.30</td>
</tr>
<tr>
<td>6</td>
<td>0.8 0.09 0.05</td>
<td>24.25</td>
<td>30.17</td>
</tr>
<tr>
<td>7</td>
<td>1.2 0.03 0.15</td>
<td>88.56</td>
<td>55.86</td>
</tr>
<tr>
<td>8</td>
<td>1.2 0.06 0.05</td>
<td>55.68</td>
<td>33.01</td>
</tr>
<tr>
<td>9</td>
<td>1.2 0.09 0.1</td>
<td>86.81</td>
<td>47.11</td>
</tr>
</tbody>
</table>
ANOVA analysis results are shown in Table 3. The ANOVA test is performed with a 95% confidence level, that is, a significant level of 5%. If the probability value (P) is less than 0.05, this indicates that the effects of the process parameters on the corresponding responses are significant (Patil et al., 2021). In Table 3, when the semantic relationship of the cutting parameters on $F_x$ was examined, it was determined that the $R$ was significant, while the $f$ was insignificant. On $F_z$, while $a$ was significant, $R$ and $f$ were found to be insignificant. According to the ANOVA results, when the contribution rates of the cutting parameters on $F_x$ were examined, it was determined that 65.61% $R$, 33.14% $a$, and finally 0.75% $f$ values were effective. On the $F_z$, it was determined that $a$ has 94.10%, $R$ has 4.32%, and $f$ has 0.49% contribution, respectively. When the semantics of the parameters on the $R_z$ roughness value was examined, it was determined that the $f$ and $R$ factors were significant, while $a$ was insignificant. In parallel with the literature, it was determined that the $f$ with 73.58%, $R$ with 24.37%, and $a$ with 1.15% contribution had the greatest effect on the roughness value.

**Table 3.** ANOVA (variance) analysis results

<table>
<thead>
<tr>
<th>S</th>
<th>DF</th>
<th>Seq SS</th>
<th>Adj SS</th>
<th>F</th>
<th>P</th>
<th>S</th>
<th>$R^2$</th>
<th>$R^2$ (adj)</th>
<th>Cont.</th>
</tr>
</thead>
<tbody>
<tr>
<td>R</td>
<td>2</td>
<td>100.989</td>
<td>100.989</td>
<td>132.30</td>
<td>0.008</td>
<td></td>
<td>65.61</td>
<td>%65.61</td>
<td></td>
</tr>
<tr>
<td>f</td>
<td>2</td>
<td>1.151</td>
<td>1.151</td>
<td>1.51</td>
<td>0.399</td>
<td></td>
<td>0.75</td>
<td>%0.75</td>
<td></td>
</tr>
<tr>
<td>a</td>
<td>2</td>
<td>51.016</td>
<td>51.016</td>
<td>66.84</td>
<td>0.015</td>
<td></td>
<td>33.14</td>
<td>%33.14</td>
<td></td>
</tr>
<tr>
<td>Error</td>
<td>2</td>
<td>0.763</td>
<td>0.763</td>
<td>0.6186</td>
<td>0.015</td>
<td></td>
<td>0.50</td>
<td>%0.50</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>8</td>
<td>153.919</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>%100</td>
<td></td>
</tr>
</tbody>
</table>
Signal to noise ratios (S/N) of $F_x$, $F_z$, and $R_z$ values are shown in Table 4. When the results are examined, the value with the highest level of the cutting parameters on $F_x$, $F_y$, and $R_z$ shows the optimum level.

Table 4. Signal to noise ratios (S/N) (Smaller is better)

<table>
<thead>
<tr>
<th></th>
<th>$F_x$ (Radial Force)</th>
<th>$F_z$ (Feed force)</th>
<th>$R_z$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Level</strong></td>
<td>$R$ (mm)</td>
<td>$f$ (mm/rev)</td>
<td>$a$ (mm)</td>
</tr>
<tr>
<td><strong>a)</strong> $F_x$ (Radial Force)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>29.79</td>
<td>-32.43</td>
<td>-29.60</td>
</tr>
<tr>
<td>2</td>
<td>-31.34</td>
<td>-33.30</td>
<td>-33.91</td>
</tr>
<tr>
<td>3</td>
<td>-37.54</td>
<td>-32.94</td>
<td>-35.16</td>
</tr>
<tr>
<td>Delta</td>
<td>7.75</td>
<td>0.87</td>
<td>5.56</td>
</tr>
<tr>
<td>Rank</td>
<td>1</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td><strong>b)</strong> $F_z$ (Feed force)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>-33.62</td>
<td>-32.86</td>
<td>-30.35</td>
</tr>
<tr>
<td>2</td>
<td>-32.54</td>
<td>-33.23</td>
<td>-33.29</td>
</tr>
<tr>
<td>3</td>
<td>-32.93</td>
<td>-33.00</td>
<td>-35.45</td>
</tr>
</tbody>
</table>

Table dimensions: Width 640px, Height 500px.
<table>
<thead>
<tr>
<th>Delta</th>
<th>1.08</th>
<th>0.37</th>
<th>5.10</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rank</td>
<td>2</td>
<td>3</td>
<td>1</td>
</tr>
</tbody>
</table>

c) Rz (Surface roughness)

<table>
<thead>
<tr>
<th>Level</th>
<th>R (mm)</th>
<th>f (mm/rev)</th>
<th>a (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-8.815</td>
<td>-5.229</td>
<td>-7.648</td>
</tr>
<tr>
<td>2</td>
<td>-6.810</td>
<td>-7.217</td>
<td>-7.097</td>
</tr>
<tr>
<td>Delta</td>
<td>2.356</td>
<td>4.410</td>
<td>0.551</td>
</tr>
<tr>
<td>Rank</td>
<td>2</td>
<td>1</td>
<td>3</td>
</tr>
</tbody>
</table>

The effects of $R$, $f$, and $a$ on $F_x$ are shown in Figure 3. Optimum cutting parameters levels and S/N ratios; $R$ (Level 1, S/N ratio: -29.79), $f$ (Level 1, S/N ratio: -32.43), and $a$ (Level 1, S/N ratio: -29.60). According to this figure as the depth of cut and tool nose radius increases the radial force also enhances. However, the feed rate does not exhibit any significant effect on the response. The significance level of the cutting parameters on $F_x$ was determined as $R$, $a$, and $f$, respectively, from largest to smallest (Table 4a).
When the main effect plot of S/N ratios in Figure 4 is examined, it has shown the optimum cutting parameters on $F_z$. Optimum cutting parameters and S/N ratios; $R$ (Level 2, S/N ratio: -32.54), $f$ (Level 1, S/N ratio: -32.86), and $a$ (Level 1, S/N ratio: -30.35). When Table 4b is examined, the effect levels of cutting parameters on the $F_z$ are determined as $a$, $R$, and $f$ from the largest to the smallest. Based on this figure, the depth of the cut has the utmost effect on the feed force. As the depth of cut increases, the feed force enhances sharply. Although tool nose radius has a minor effect on the response, feed rate has no effect.

**Figure 3.** Effects of cutting parameters on $F_x$
The impact of $R$, $f$, and $a$ on $R_z$ are shown in Figure 5. Optimum surface roughness parameter and S/N ratios; $R$ (Level 3, S/N ratio: -6.459), $f$ (Level 1, S/N ratio: -5.229), and $a$ (Level 2, S/N ratio: -7.097). The order of effectiveness of the cutting parameters on the roughness value was determined as $f$, $R$, and $a$, respectively, from the largest to the smallest. As the feed rate increases due to the metal cutting theory, the surface quality deteriorates. In contrast, as the nose radius enhances a better surface quality is obtained. The effect of depth of cut on $Ra$ is negligible.
Figure 5. Effects of cutting parameters on $R_z$

Figure 6 shows the interaction graphs on the $F_x$, $F_z$, and $R_z$ values of the cutting parameters with the most impact. When Figure 6a and Figure 6b were examined, it was determined that the $F_x$ and $F_z$ values increased as the $a$ increased. Therefore, as the chip thickness increases, the cutting tool needs more force to break the chip off the workpiece. Therefore, as the chip thickness increased, the cutting forces increased. The increase in the main shear force with the increase of feed rate and depth of cut can be explained by the Kienzle equation. Here, increasing chip cross-sectional area due to the increase in $f$ and $a$ causes an increase in cutting forces (Çakır, 2000; Iynen et al., 2020a). In Figure 6b, it was determined that the $F_z$ value decreased when the $R$ increased and the $F_z$ value increased when the cutting depth value increased.
In Figure 6c, it was determined that the roughness value \( R_z \) increased when the \( f \) value was increased. This situation emerges in parallel with the literature. In the literature, it is emphasized that an increase in the \( f \) will negatively affect the surface roughness (Yaşar et al., 2020; Iynen et al., 2020b; Başak and Baday, 2016; Günay, 2013; Gürbüz et al., 2020; Şahinoğlu and Rafighi, 2020a; 2020b; Koçak, 2020; Kam and Demirtaş, 2021). It is seen that the roughness values are better in the experiments performed with a low \( f \). In general, the \( R \) and the roughness value are inversely proportional. As the \( R \) increases, the roughness value decreases. This means that as the \( R \) increases, the amount of friction on the material also increases. Due to the increased friction between the tool and the workpiece, the specific cutting resistance of the material will decrease and the chip will be removed from the material more easily. For this reason, it is thought that there is a decrease in the surface roughness value.

![Figure 6. Cutting Parameters Interaction Graphs, a) Fx, b) Fz, c) Rz](image-url)
Figure 7 shows the 2D contour graph for radial force, feed force, and surface roughness. The effects of the 1\textsuperscript{st}, 2\textsuperscript{nd}, and 3\textsuperscript{rd} level values of the cutting parameters on the $F_x$, $F_z$, and $R_z$ values are shown in the contour chart. When the graph is examined, the red-colored regions show the parameter limits where the lowest cutting force and surface roughness values are obtained.

![Figure 7. 2D Contour Plots](image)

Probability graphs for the model residuals of radial, axial force, and surface roughness are shown in Figures 8a, 8b, and 8c. According to this graph, almost all cutting force residues are very close to the centerline, with no intersection of the upper and lower deflection curves. For the surface roughness model, the residues are within an acceptable range with respect to the centerline. Therefore, the difference between actual and predicted results is not large. Thus,
these graphs confirm that the models developed are suitable for predicting responses.

![Graphs showing probability plots of Fx, Fz, and Rz values.](image)

**Figure 8.** Probability plots of $F_x$, $F_z$, and $R_z$ values

**CONCLUSION**

In this study, the effects of cutting parameters ($R$, $f$, and $a$) on cutting forces ($F_x$ and $F_z$) and surface roughness ($R_z$) were investigated experimentally in dry turning of AISI 4340 steel. The obtained results are presented as follows:

- There is a direct relationship between $f$ and average $R_z$. As the $f$ increased, the $R_z$ is also increased. Contrary to $f$, as the $R$ increases a good surface quality is obtained.
- In order to obtain the optimum $F_x$; It was determined that the following cutting parameters should be selected: $R$: 0.4 mm, $f$: 
0.03 mm/rev, and \( a \): 0.05 mm. In addition, it has been determined that the \( R \) and \( a \) are effective in approaching the minimum conditions of the \( F_x \) value.

- In order to obtain the optimum \( F_z \) value; It was determined that the following cutting parameters should be selected: \( R \): 0.8 mm, \( f \): 0.03 mm/rev, and \( a \): 0.05 mm. In addition, it was determined that the \( a \) and \( R \) were effective in approaching the least value of the \( F_z \).

- In order to obtain the least \( R_z \) value; It was determined that the following cutting parameters should be selected: \( R \): 1.2 mm, \( f \): 0.03 mm/rev, and \( a \): 0.10 mm. In addition, it has been determined that the \( f \) and the \( R \) are effective in approaching the minimum conditions of the \( R_z \) value.

- It was determined that the parameters that affect the cutting forces the most at constant cutting speed are \( R \) and \( a \).

- \( F_x \) value; while the \( R \) is the most effective parameter, it has been observed that the \( R \) situation is second-order effective for \( F_z \) and \( R_z \).

- \( F_z \) value; while the \( a \) was the most effective parameter, it was observed that depth of cut was the parameter with the least effective for the \( R_z \) value.

- \( R_z \) value; while the \( f \) was the most effective parameter, it was observed that \( f \) was the parameter with the least effect for \( F_x \) and \( F_z \).
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CHAPTER 4

A NOVEL IMAGE SEGMENTATION TECHNIQUE FOR MEDICAL DECISION SUPPORT SYSTEMS: OSTEOARTHRITIS (OA) KNEE ABNORMALITY DETECTION FROM HAZY X-RAY IMAGES THROUGH POLYGON CONSTRUCTION BASED ON CONNECTED LINE SEGMENTS

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While Starting

In the health informatics area, illness and disorder detection of knees through X-Ray images plays an important role in the field of clinical decision support systems. The major problem in segmentation of X-Ray images is commonly known as the chaotic noise distribution through the images. The local minima regions which have the minimum amount of intensity deviations cause problem due to lack of image information. The scope of this study is to segment X-Ray images by detecting the true line segments in each patch and then make true connections of line segments depending on their orientation and statistical shape prior image information. For this purpose, a minimum variance based median filter is developed for smoothing the X-Ray images while preserving the edge lines in order to maintain the image quality. The idea is taken from MCV (minimum coefficient of variation) and MLV (mean least variance) filters which perform the same operation with the Mean Filtering algorithm. Different from the conventional Median Filter, this filter keeps the original edge lines while the kernel size is increased. Since the Median Filter is considered as the best filter to keep the edge pixels, a median filtering is applied to the regions with low-variance. Additionally, the Haar Wavelet Transform (HWT) is employed horizontally and vertically to eliminate the low-frequency variance values in the kernel region. The kernel size is supposed to be the power of 2 for getting robust results due to the structure of the HWT. Finally, a simple connected points algorithm is employed to eliminate the noisy edge pixels. Finally, obtained edge pixels are employed to construct line segments in each
patch. Finally, the intersection of the line segments is achieved depending on the Euclidean distances and acute (inner) angles among line segments. A simple graph structure is employed to keep the connectivity of the line segments and image segmentation is achieved with the connected line segments that makes a polygon. Successful experimental results have been taken throughout the empirical studies. However, misconnections among line segments still continue which is the major problem of the proposed method. The proposed method is novel and can be useful for other researchers to fix the existing problems.

1. INTRODUCTION

Osteoarthritis is a common symptom in people over the age of 40. It happens in the knee joints and this abnormality can cause the articular cartilage to tear and the bone to rub painfully against the bone. Orthopedic surgeons recommend that patients take x-rays of their joints to diagnose osteoarthritis.

In Dorland's Medical Dictionary (Dorland et al., 1957), osteoarthritis (OA) (Felson et al., 2006) is defined as degenerative arthritis or degenerative joint disease that consists of a group of mechanical abnormalities that involve the breakdown of joints, including articular cartilage and subchondral bone. Figure 1 illustrates a sample X-Ray image which shows the primary stage of OA with narrowing joint space and increasing bone density as follows:
Detection of OA plays an important role in medical activities for robust treatment. Therefore, evaluation of the images is the most important part of the detection analysis which is dependent on the quality of techniques used in terms of image processing. Five-scale Kellgren-Lawrence grading technique (Riyazi et al., 2005) is the best known method for the evaluation section, where the assessment is based on the degree of osteophyte (bone spore) formation (Finzel et al., 2014), narrowing of the joint space and sclerosis (change of the bone tissue around the joint) and the joint deformity (Nakayama et al., 2016). In this scale,

- 0 = Normal OA.
- 1 = Doubtful OA.
- 2 = Minimal OA.
- 3 = Moderate OA.
- 4 = Severe OA.
In the literature, there are some related academic studies in this particular research field. Various image processing methods have been applied on knee diseases to enhance the image quality. Gornale et al. has made a literature review study in 2016 about the image processing algorithms used for the classification and exploration of osteoarthritis diseases (Gornale et al., 2016). In the study, various medical imaging methods for the detection and evaluation of osteoarthritis in the X-Ray and the Magnetic Resonance Imaging (MRI) are reviewed. Additionally, a plenty of feature extraction methods, segmentation techniques, and classification schemes regarding Osteoarthritis (OA) are presented and compared.

Lately, Saleem et al. (Saleem et al., 2020) has presented a study regarding a computer-vision-based system which automatically assists radiologists by analyzing possible radiological symptoms in knee using X-Ray images. According to their outputs, 97% accuracy is obtained over a large knee X-Ray image dataset for the sake of robust osteoarthritis detection.

In another study (Bharodiya et al., 2021), an intelligent algorithm, whose name is WODJSW (wrist osteoarthritis detection using JSW), is proposed to assist an orthopedician diagnose and measure the joint space width (JSW) in the X-Ray images automatically. Their method achieves an approximate 96% diagnosing accuracy on the 75 number of X-Ray test images.

Recently, a statistical image processing technique is introduced in terms of handling robust detection of joint abnormality (Tiulpin et al.,
In the study, the authors simply load the knee joint X-ray images and pass the image through a noise filter and edge detector which finally outputs a clear border image to be used in Kellgren-Lawrance scale which inputs the distances between particular joint segments. They developed KOACAD (Knee OA Computer Assisted Diagnosis) system which automatically detects the OA through image processing. According to their saying, the system is robust on the data of 6,000 cases. However, this method requires a robust and precise detection of joint boundaries for true evaluation. Basically, they employ median filter for noise reduction which is very good at preserving edge points while smoothing the noisy regions. Other noise filters such as Laplacian Gaussian (Mohamad et al., 2018), Sobel (Yaman et al., 2019), Prewitt (Fakhri et al., 2019), Roberts (Kang et al., 2008), Canny (Rahman et al., 2020) edge detection algorithms assume the fact that small regions have Gaussian distribution in terms of intensity, however, the X-Ray images are hazy and the noise due to haze in images ruin the Gaussian distribution in most of the cases which finally causes rough edge detection while missing the local minima regions. On the other hand, median filter preserves the edge lines robustly unless the filter size is increased significantly. The more the filter size is increased, the more noise will enter to filter which cause wrong detection. Since they employ a statistical framework, they need to get all the single edge details which can be handled only by median filter. After getting the edge lines, they use a particular connected points algorithm in order to obtain a clear boundary image which takes place as an important step in their algorithm.
To sum up, image processing is the key tool for handling the boundary regions which rates the abnormality levels depending on the distances among particular joint segments. For this reason, robust image filtering for eliminating the noise in the hazy X-Ray images is required while detecting the edge pixels accurately in order to detect line segments and construct a polygon to segment the image portion with OA. Therefore, image processing field is crucial for this particular research problem to enhance the current systems.

Among all the filters, the Median filter is known as it is the best to preserve the edge regions while smoothing; however, the thickness of edge regions also increases while increasing the kernel size (Erkan et al., 2018). An optimal filter should smooth the image while keeping the edge lines originally with 1 pixel-width.

In this study, instead of using intensity values to optimize a filter, the absolute variance values of each pixel are employed which are defined as the absolute deviation from the median of any 2D patch. In order to preserve the edges while smoothing, the adjacent patches of any central patch are searched and the patch with the minimum absolute variance is found and its median intensity value is assigned to all the pixels in the central patch. Afterwards, the Haar Wavelet Transform (HWT) is employed on the variance values of each patch and the edge regions with low-frequency variance values are eliminated for robust edge detection. In order to perform an edge detection in each patch, a 3x3 Sobel kernel is run through each patch and detected edge pixels are latterly employed in the line segment detection module which is
achieved by using RANSAC grouper. RANSAC grouper (Hirzer et al., 2008) is a statistical line detection method which generates all the possibility of combination of points that make a line and group them with respect to their similarity in slope which finally results the best line fit better than the least square regression method. Later, detected line segments are combined with respect to some specific intersection rules and polygon detection is achieved by using a simple graph structure. This study differs from the previous studies mentioned in the literature by proposing a novel method which uses the line segments rather than the edge points, and employs the connected line segments instead of the connected edge points which reduces the speed and time complexity significantly. Additionally, the proposed method outputs successful results on the boundary segmentation of osteoarthritis (OA) knee abnormality through hazy X-Ray images which is the fundamental step to develop a machine learning based clinical decision support system in this regard.

This paper has three more sections. In the second section, materials and methods are described in detail. Experimental results are presented in the third section. In the fourth section, conclusions are summarized.

2. MATERIALS AND METHODS

This study evaluates intensity deviations and shape convergence to the shape prior in multi-resolution paradigm. Multi-resolution is performed by getting the variance image starting from the maximum threshold to the minimum thresholds which are pre-defined. Through
this aim, necessary edge enhancers are also used. A dynamic patch size paradigm has been added to the system. Processing of each patch region only one time is programmed and the regions with no edge pixels where variance threshold is 0 are removed from the candidate line segments’ list to increase the processing speed. An edge enhancer algorithm is developed by filtering the 8 neighborhood variance values through Haar-Wavelet Transform which removes the low-frequency values in variance array with size=8.

The reason why the HWT is preferred for signal boosting is the fact that the HWT convolution is used for discrete signals. Since median filtering is not a Linear Shift Invariant System (LSIS), it is impossible to create a convolution operation from Median filtering which means that median filtering cannot be formulated linearly. Therefore, it is well-known that it's a non-linear discrete signal. Additionally, a local filtering can be performed in discrete signals only by looking at the neighborhood relations.

On the other hand, various filtering types can be applied to continuous functions such as Gaussian, Mean, Sobel, and Laplace etc. They can be linearly modelled and convolved through particular kernels whereas median filtering cannot be modelled and cascaded through linear kernels. Therefore, HWT can be easily applied in median filtering in which sorting operation is a must in the algorithmic context. In order to find the middle value, that is, the median value, it is necessary to sort. When the HWT is applied to the kernel, the HWT keeps the values that have been transformed, that is, convolved, it also
keeps these data in order and obtains the average value at the last step. After dumping the discrete signal with a certain threshold and apply the deconvolution operation again, the signal is boosted and strengthened. In other words, it reduces the dynamic range of the input signal by approximating the small changes (zig-zags), and finally outputs a smoother signal.

Due to the nature of HWT, the number of elements in the input signal must be 2 power of N. In other words, since the images are 2 dimensional, therefore employed kernels should be 2 dimensional as well, in this regard, only the kernels with 2 power of N elements can be employed in the HWT model. For instance, if the kernel size is 2, then, there will be a total of $2 \times 2 = 4$ elements horizontally and vertically, and it fits to the HWT model since 4 is equal to the 2 power of 2. On the other hand, the standard kernel sizes that are employed in the conventional filtering types such as 3, 5, 7, 9, 11, 13, and 15 etc. cannot be used in the HWT model. Instead, the kernel sizes such as 2, 4, 8, 16, 32, 64 etc. can be used in HWT model. However, when this happens naturally, the kernel does not exactly sit on the central pixel. For instance, where will the central pixel be at kernel size is 2? If the central pixel has to sit right in the middle of the kernel, but in this way, there is 1 space on the right and no space on the left. If the kernel size is 3, there would be 1 pixel on the right and 1 pixel on the left and there would be no problem. Therefore, even numbered kernel sizes cannot be used in filtering operations. But due to the nature of HWT, the kernel has to be an even number which is also a research problem particularly solved in this study.
An adaptive boosted median filter is developed for smoothing the image while preserving the edge pixels. Different from the conventional median filter, this filter keeps the original edge pixels while the kernel size is increased. It also boosts the low frequency variance values which yields robust edge detection in higher variance thresholds. Later, the connected point’s algorithm is applied to the edge detector to eliminate the short-length connected edge pixels. The idea is to remove the unconnected regions. To achieve that, the sizes of the cluster vectors are used as a threshold value to get the desired length of chain. A 3x3 connection kernel is created to make an optimum connection between the central line segments with each of the two other adjacent line segment pairs.

Since one central line segment can connect to 28 numbers of pairs in a 3x3 connection kernel, a geometrical approach is used to find the best probable connection in 8 neighborhoods. Additionally, a grid of two-dimensional image with a certain patch width and patch height is constructed to achieve the intersection of crossing segments of extended lines which have a coherent extension through each central patch. Two previously introduced algorithms are used for this purpose as the extended version of the Bresenham’s Line Drawing Algorithm and the Cohen-Sutherland Line Clipping Algorithm which are merged and employed together to clip the extended line segments through each extended patch regions inside the input X-Ray images. A snapshot from this simulation is illustrated in Figure 2 as follows:
Both are pixel-wise, so they are transformed to patch-wise context. RANSAC grouper is employed for the optimum line segment estimation in multi-resolution paradigm. To determine the stop criteria of iteration part of RANSAC grouper, eigen-values of hessian matrices of the patch regions are calculated and the eigenvectors are oriented. By using the orientation slopes, RANSAC grouper is finalized and it increases the speed and accuracy of the proposed method apparently. Boosted median filtering method is modified in terms of variance information of each window. Instead of using the average variance in the covariance matrix, the hessian matrix is used to estimate the energy of variance and coherency of the window. The multiplication of variance energy and coherency yields better results than the previous one. RANSAC Grouper is modified to create a linear model
in which the slope coefficient comes from the orientation value of eigen-vectors through each patch region. However, eigenvectors are not calculated from the still image, instead; in each variance threshold (multi-resolution), the eigenvectors of each region is calculated. Hence, noise cannot affect the robustness of eigenvectors. Noise comes when the variance threshold is very low such as 2, 1, and 0, generally. By this method, most robust eigenvectors are used to model the linear model in RANSAC grouper. Afterwards, a curvature based Active Contour Snake Model is created by defining the shapes prior with combination of line segments of each patch. Fourier Shape descriptor is employed to create unique combinations of Fourier coefficients. Snake deformation chooses the correct connections to complete the shape prior. The difficult part is the relation between number of snake nodes and number of Fourier shape nodes. This method dramatically increases the robustness of the line segments’ connectivity which is the most important part of the whole study.

2.1. X-RAY IMAGE SEGMENTATION BY USING CONNECTED LINE SEGMENTS

Maximum intensity variation from the central pixel among 8 neighbors is used for the edge detection part. Instead of using intensity threshold, this algorithm uses variation threshold. Because in every case; varying illumination and rotation; the proposed algorithm always works fine if the variation threshold is satisfied. If the input image is divided into square patches; then it is possible to detect the line segments with Least-Square Linear Regression or RANSAC grouper
and as many others. In this study, the RANSAC grouper is employed in this purpose since it has a clustering algorithm in itself and gives better results. Since the line segments are detected through each patch in the image; optimum intersection rules are to be defined in order to make proper connections among each detected line segments in 3x3 patch neighborhood. Since in a single 3x3 patch neighborhood, there are 28 number of possible connections which is mathematically denoted as $C(8,3)=28$ in which two neighbor patch connects with the central patch, the summation of the acute angles are to be minimized for the optimum connection selection illustrated in Equation 1 and Figure 3, respectively as follows:

$$\min_{i=\text{Combination}[1,28]} (a_{i_1} + a_{i_2} + a_{i_3} + a_{i_4}) = \text{Optimum Connection.} \quad (1)$$

**Figure 3:** Acute angles to be minimized in the summation out of 28 number of combinations
Additionally, there are several rules defined to make these optimum connections as follows:

- **Rule 1** - Every line segment can intersect only one time; just one time with its one end-point.
- **Rule 2** - If line segments are parallel; there will be no intersection. (The dot product is 1)
- **Rule 3** - If line segments are parallel, but they are on the same line, then; they can intersect.
- **Rule 4** - If line segments are perpendicular to each other (dot product is zero), then; they will fulfill each other. If they are not perpendicular each other; then the shortest distance between two line will determine the intersection point.

\[
\text{If ( shortestDistance < distanceThreshold ) Then}
\]
\[
\text{intersectionPoint.x = (p1.x+p2.x) * 0.5f;}
\]
\[
\text{intersectionPoint.y = (p1.y+p2.y) * 0.5f;}
\]
\[
\text{End If}
\]

- **Rule 5** - If there is a proper intersection; connect the two line segments and put into the graph node. Every single node can intersect only one time. If the initial node is same with the last node; then; it means that connected line segments formed a polygon and a polygon is detected. Additionally, each patch size is dynamically increased starting from an initial patch size and increases by an increment value while the thresholding value converges to zero.

\[
\text{for( thresholding=maxThresholdValue; thresholding >=minThresholdValue; thresholding -- )}
\]
\[
\{
\text{Patch_size++;}
\}
Check the slope difference between enlarged line and current line in each iteration step until the difference converges to zero or 180. (In each step, increase the path size by 1)

Check processedRegion (int enlarged_Patch_size, current) -> if false THEN
Find edges and lines in the enlarged patch.
}

2.2 ZIPPER METHOD

The aim of the algorithm is to find the true path of intersections among pool of lines which are stored in a vector. Because the lines are stored to vector starting from the higher variance threshold to the lower threshold, neighbor lines indexed in the vector have the highest similarity in slope and minimum distance to each other which results in a priority for intersection. Therefore, this method is named as “Zipper Method” which increased the processing speed and the accuracy dramatically. The illustration of the proposed “Zipper Method” is shown in Figure 4 as follows:

![Figure 4: Infra-structure of the Zipper Method](image)

If neighbor lines do not intersect, the next line will be never tested for any intersection. It is the wrong way of zipper. So it is removed from the repository of lines.
3. EXPERIMENTAL RESULTS

Experimental and benchmarking studies have not been performed yet; however, from human-eye glance; results are encouraging. Apparently, even we increase the kernel size, edge lines are not increasing in thickness and this is a very good development in edge detection. Other noise filters such as Hessian filter, Laplacian Gaussian, Sobel, Prewitt, Roberts, Canny edge detection algorithms are increasing the edge thickness when the kernel size increased. However, our filter keeps the original edge thickness while the filter size is increased.

Latterly; we plan to evaluate the method with several benchmarking methods. The evaluation parameters have not been decided yet; however; simply; they may be such as: edge thickness, correlation with the manually segmented image and speed. When we apply the conventional median filter with the kernel size of 8 and the variance threshold of 4, the edges are detected with enlarging thickness and some missing parts of the image. However, the proposed method with the same parameters keeps the original edge thickness and enhances the variance frequencies which reveals the missing parts with noisy regions. In order to eliminate the noisy regions, we apply the connected point’s algorithm and the results are encouraging. After these, a patch-wise line segment detector is applied through the image and intersections are constructed with respect to the intersection rules in multi-resolution paradigm in which edge pixels are detected in higher thresholds and while detecting the edge line segments in less
noisy regions, zipper method works and construct the connected line segments to make a complete polygon. This is the basic philosophy of the proposed method. Several experimental snapshots are illustrated below in Figure 5 and Figure 6, respectively as follows:
**Figure 5:** Intersected Line Segments with respect to Intersection Rules (Initial Patch Size is 24)

In case of initial patch size is 24 pixels; the details are lost dramatically in the image which results in wider angles through joints which make intersection rules apply in difficult way. Additionally, at the right picture, dynamic patch systematic is also illustrated which depicts how the patches dynamically adapts to the nature of the belonging patch of each line segment. In this regard, each line segment is iteratively extended till the slope changes dramatically. After that, Bresenham’s Line Drawing and Cohen-Sutherland’s Line Clipping algorithms are applied and eventually
extended line segments are clipped and allocated to their proper patch positions. This increases the accuracy of the proposed method.

Similarly, Figure 6 illustrates the same philosophy in a more detailed version in which the initial patch size is 12 pixels as follows:
To sum up, the obtained edge pixels are employed to construct line segments in each patch. Finally, the intersection of the line segments is achieved depending on the Euclidean distances and acute (inner) angles among line segments. A simple graph structure is employed to keep the connectivity of the line segments and image segmentation is achieved with the connected line segment that makes a polygon. According to the experiments have been taken, misconnections among line segments still continue which is the major problem of the proposed method. The proposed method is novel and can be useful for other researchers to fix the existing problems.
CONCLUSION

The scope of this study is to see the actual line segment in each patch, divide the X-ray image and actually connect the line segment based on the direction and statistical shape model information. For this purpose, a minimum variance-based median filter is developed to smooth the X-ray image while preserving the edges to preserve image quality. Unlike conventional median filters, this filter retains its original borders as the kernel size increases. Median filtering is used in areas with low scatter because the median filter is considered to be the best filter to preserve edge pixels. It also uses the Haar Wavelet Transform (HWT) horizontally and vertically to remove low frequency variance values in the kernel area. The size of the kernel must be a power of 2 due to the structure of HWT to get strong results. Later, a simple connection algorithm is used to remove the noisy edge picks and line segments are detected in each patch through RANSAC Grouper. Finally, the line segments are cut according to the acute angle (inner angle) between the Euclidean distance and the line segment. A simple graph structure is used to maintain the connection to the line segments, and the polygonal line segments are connected together to achieve image segmentation. Successful experimental results have been obtained through empirical research. The biggest problem with the proposed method, however, is that incorrect connections between lines still persist. The proposed method will help other new researchers solve existing problems.
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BÖLÜM 5

REMOTE MONITORING OF MUSCLE SIGNALS WITH EMG SENSOR

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INTRODUCTION

Musculoskeletal system diseases have become one of the most important health problems related to work and social life, frequently seen in working societies. Musculoskeletal diseases include a wide range of inflammatory and degenerative conditions that can occur due to single or accumulated trauma and affect muscles, ligaments, tendons, nerves, bones and joints. Musculoskeletal diseases, which are the leading causes of pain and loss of function, cause different levels of deterioration in the quality of life (Tunçay, Yeldan, 2013, Şirzai, etc, 2015). The human body has a biomechanical structure that can easily adapt to different postures and activities. It works best by moving and changing positions. Muscles are designed to contract actively. Pumping and blood flow will also be impaired when the muscles remain tensely contracted. Sitting for long hours and standing in a bent position can cause muscle fatigue and a decrease in blood flow due to pumping insufficiency (Atasoy, etc, 2010). In upper extremity musculoskeletal diseases, pain, swelling, stiffness, tingling, loss of sensation, loss of strength and coordination, skin changes, temperature differences and loss of function in both work and daily living activities are observed (9). Discomforts such as adhesive capsulitis, epicondylitis, carpal tunnel syndrome, ulnar neuropathy, tendinitis, neck pain are quite common in the upper extremity (Şirzai, etc, 2015). The human neuromuscular system provides a flexible and stable movement capability with minimum energy consumption by constantly changing the stiffness and damping in the joints it controls. (Kılıç, etc., 2021). One of the most effective methods in the detection
of musculoskeletal diseases and the measurement of muscle contraction energy is the use of bioelectrical signals. EMG signals carry information about the neuromuscular muscles and are suitable for use as a control signal in prosthetic devices (Taşar, etc., 2018). The body uses muscles when performing physical movements. A contraction action begins with the stimulation of the motor nerve cell by the nervous system. The stimulus is transmitted to the muscle cells via the neuromuscular junction. The action potential generated in the muscle cells spreads through the muscle through the adjacent cells forming the muscle fibre. These action potentials create the bioelectric signal. Although bioelectric signals differ according to the tissues and organs from which they originate, they generally have common features such as low amplitude ($10 \mu V - 10 mV$) and low frequency ($0-200 Hz$). Electrodes, amplifiers, signal adaptors, and signal display tools are used to measure these signals, which are of very small amplitude. Surface electrodes, which are attached to the skin, are commonly used as electrodes because they do not damage the tissues (Küçük and Mayetin, 2016). EMG is frequently used in many medical fields today and is an assessment tool for analyzing muscle function. With the help of this measurement technique, which contains important information about the contraction of our body muscles, it is checked which muscles are activated in which movement (Eser, 2018). In this study, remote monitoring of muscle signals with an EMG sensor was performed for individuals suffering from muscle disorders due to different reasons (accident, genetics, injury, etc.). With the designed system, the contraction signals of the user's upper
limb arm muscle were instantly sent to the thingspeak web address, which is used for the internet of things platform. In the Thingspeak IoT platform, these data were converted into graphs. Remote monitoring of the user's signals during muscle contraction was performed.

1. MATERIALS AND METHOD

1.1. Internet of Things (IoT)

The American Federal Trade Commission defined the Internet of Things as "the ability of objects in daily use to connect to the Internet and send and receive data" (Öcal, etc., 2018). The concept of the Internet of Things is used in many areas of daily life because it provides technological convenience today. Although it is becoming widespread day by day and its usage area is increasing, it does not have a common definition. ITU (International Telecommunication Union) defines the Internet of Things as a global infrastructure for the information society that connects all kinds of objects/things based on existing and interoperable information and communication technologies (Şengül, 2018). The Internet of Things is a system of devices. With this communication system, which was created depending on the communication of many different devices over a network, objects have gained the ability to interact with each other. Not only internet technology but also RFID (Radio Frequency Identification), in other words, interactions performed via radio frequency identification technology are also included in the internet
system of objects. RFID is the technology of transferring data from objects with an electronic RFID tag, using radio waves, through an RFID reader. Data is collected and transmitted in real-time. With the RFID tag, objects are given their unique identity. Apart from RFID, digitized data received from an adapter connected to the server, in other words from the sensor, can also be transferred wirelessly using the standard IP Protocol (Kılıç, etc., 2017). In short, IoT is technological sense organs and sensors that provide data exchange and connection functions to devices (Akleylek, etc., 2020). The Internet of Things (IoT) is used in many areas such as health, energy, urbanism, environmentalism, agriculture, livestock, shopping, logistics, measurement systems, industrial control, security and emergencies (Gökrem and Bozuklu 2016). This is an area that needs to be dealt with. Either for rapid intervention or early diagnosis, the patient should be kept under constant surveillance, which has limitations, these are some value changes that the specialist cannot understand by observation. In the Internet of Things, continuous values are taken from the patient and when there is a negative change, the specialist is immediately notified and rapid intervention can be performed (Çalışkan, 2018). In addition, with the IoT technology used in the field of health, remote monitoring of medical parameters can be done easily. Remote monitoring of the exercises that orthopaedic patients and athletes should do is among these popular applications (Çoban and Aktaş, 2020). In this study, remote monitoring of EMG sensor data was carried out. EMG sensors were attached to the individual
who had muscle discomfort due to certain reasons and instant data was taken depending on the muscle movements during the day.

1.2. Thingspeak IoT Platform

ThingSpeak is a free data platform designed for the Internet of Things. It collects and stores data in real-time. It allows this data to be analyzed and visualized with MATLAB. At the same time, it can be easily integrated with other platforms thanks to its applications and API keys. (Sazak and Albayrak, 2017). Thingspeak is a free data platform for the Internet of Things (IoT) that remains popular today. Thingspeak is also a web-based open API IoT-based information platform that converts external components used for IoT into their data and is used to store sensor data. Thingspeak communicates between the internet connection and the cloud as a 'data packet' carrier and takes the detected graphic from the connected sensor to the main microcontroller, records, analyzes, observes and works. Thingspeak Arduino, TI CC3200 module, Raspberry-pi etc. It helps build the social network of development photos, sensor-based daily apps, location/location tracking apps, and updated objects. The main feature of the Thingspeak function is the Data field, location field, Channel field, which is the status field. Thingspeak, mechanical mechanisms can be created, the information you choose and information can be processed and visualized alternately and matched with MATLAB's use of tweets and other warning forms. It also offers the ability to create a general channel for general analysis and forecasting. It takes advantage of graphic visualization operations for sensors/actuators
and can be used for objects. IoT helps bring everything together and allows us to communicate with our things, and more interestingly, allows objects to interact with other objects. This is the platform. Thingspeak offers the use of real data, graphic visualization, as well as plug-ins used to collaborate with web services, social networks or API. The main feature of Thingspeak is the Thingspeak Channel. On a page that will send the channel to Thingspeak for channelling. Programs loaded on the microcontroller transmit to the thingspeak channel within a certain period on the sensor screen. Programs uploaded to the microcontroller have a 15-second period to transmit the latest sensor values to the Thingspeak Channel. As the internet of things progressed, the wireless sensor network became more and more acceptable. As the Internet of Things progresses, the wireless sensor network is used. (Ersin and Öz, 2020).

1.3. Design of IoT System

In this study, remote monitoring of muscle signals was performed. In the designed system, an EMG sensor was used to receive muscle signals. The EMG sensor is attached to the upper limb of the person with the disorder. The EMG sensor is a sensor module that connects to various points of the human body and reads the electrical signals created by the muscles and nerves in those areas with microcontroller systems. The sensor, which gives a signal output of 1.5V in the idle state, increases up to the voltage level of 3.3V with muscle contraction. The sensor output works as an analogue voltage output. There are 3 muscle probes in the EMG sensor used in the system. The red and white probes are used to measure the muscle values in the
upper limb and the black probe is used to take the reference value. A microcontroller development board is used to control the values received by the EMG sensor. The ESP8266 wifi module is attached to the microcontroller development board to send the data from the EMG sensor to the Thingspeak IoT web service. The block diagram of the system is shown in figure 1.

![Block diagram of the system](image)

Figure 1. Block diagram of the system

In this study, the connection of the EMG sensor and the electronic connection structure of the system is shown in Figure 2.
EMG sensors in the system take different values according to the movement of the person's arm. The image of the EMG sensor attached to the user's arm is shown in figure 3.
The values received by the EMG Sensor are sent to the thingspeak internet address in real-time with the ESP8266 wifi module. The image of the received data in serial communication is shown in figure 4.
A channel has been created in the Thingspeak IoT platform for this data to come. The key of the channel and the IP address of the thingspeak IoT platform is coded with the microcontroller software. The EMG sensor receives data according to the movement of the person's arm and instantly sends this data to the Thingspeak IoT platform. The graphical display of the data received by the system is shown in Figure 5.
Instantly incoming data to the Thingspeak IoT platform via ESP8266 wifi module is kept here and converted into graphics on the channel. Thanks to the graph in the Thingspeak channel, values such as the amount of contraction of the person's muscle, the intervals at which it contracts, the maximum contraction, and the minimum contraction can be reached. The person's upper limb muscle contraction and weekly or even monthly results can be followed again via the thingspeak channel. The graphical image of the channel opened on the Thingspeak IoT platform and the instantaneous data are shown in Figure 6.
With this study, the physical therapist will be able to follow his patient remotely, thanks to the thingspeak IoT platform data. In addition, thingview, the android software of the Thingspeak IoT platform, was also used in this study. The data coming to the Thingspeak IoT platform can be tracked with any android device thanks to this software. Thanks to this system, the physical therapist will also be able to reach the muscle contraction values of the person with muscle disease with an android device. The screenshot of the thingview software, which is the android software of the Thingspeak IoT platform, is shown in figure 7.
The exercises that the person with muscle disease should do can be followed with this system. Data such as what time of the day the person exercises, how long he exercises and the amount of muscle contraction will be able to reach in real-time.

Figure 7. Thingview android software screenshot
2. RESULT

With the increasing population and busy life, the number of individuals suffering from muscle disorders is increasing day by day. In this study, remote monitoring of muscle contractions in the upper limb arm is caused by certain reasons (accident, injury, old age, muscle weakness, etc.) Remote monitoring of intramuscular contractions of individuals with muscle disease was performed. With this study, a graphical view of the EMG sensor data was provided instantly in the thingspeak and thingview android software. The electronic circuit structure of the system was created and the microcontroller codes were written. The EMG sensor located on the upper limb of the person instantly measured the muscle signals and transmitted these data to the thingspeak channel with the ESP8266 wifi module. The system was tested on a user and 105 data were received. Depending on the person's muscle signals, the amplitude values of approximately 270 to 350 have been determined. The data were followed graphically in the thingspeak IoT web service. With this study, the amount of muscle contraction and the time intervals of the individual experiencing muscle discomfort can be seen graphically. Thanks to the study, the physical therapist will perform the exercise of the individual patient (how long he does it, whether he does it right or wrong) or the patient's muscle follow-up.
REFERENCES


Çoban, G., & Aktaş, F. Ortopedi Hastaları Ve Sporcular İçin Nesnelerin İnterneti Tabanlı Hareket Takip Sistemi Iot-Based Motion Tracking System For Orthopedic Patients And Athletes.


CHAPTER 6

IMPROVED PERFORMANCE OF YEAST LOCALIZATION PREDICTION BY BALANCING WITH DBSCAN AND WEIGHTED ARITHMETIC MEAN

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INTRODUCTION

Machine Learning (ML) techniques are widely used in data science such as biological data analytics to understand and classify data (Xu & Jackson, 2019). One of the known ML is Supervised ML techniques that are trained by the data to extract meaning and classify which strongly correlated with the properties of the data, so the definitive data which represents the purpose better becomes crucial to increase the ML performance. One of the definitive properties is the balance between labels. It is common that the collected biological data has been imbalanced by means of labels. Thus, the imbalanced data has significant damage to the performance of ML algorithms. Imbalanced data indicates that the majority class is more prioritized in classification methods, and the minority class is generally deprioritized (Sun, Wong, & Kamel, 2009). Thus, increasing the number of misclassified cases diminishes the accuracy of the predictive model (Chawla, Japkowicz, & Kotcz, 2004). To enhance prediction accuracy, classes could be balanced by various methods. Several methods are introduced to prevent performance loss such as All KNN (KNN) (Tomek, 1976), Cluster Centroids (CC) (Pang & Jiang, 2013), Condensed Nearest Neighbor (CNN) (Hart, 1968), Edited Nearest Neighbors (ENN) (Wilson, 1972), Near Miss (NM) (Mani & Zhang, 2003), Neighborhood Cleaning Rule (NCR) (Laurikkala, 2001), Random Under Sampler (RUS) (Radivojac, Chawla, Dunker, & Obradovic, 2004), Repeated Edited Nearest
Neighbors (RENN) (Tomek, 1976), and Tomek Links (TL) (Ivan, 1976). The listed methods are known and implemented in python libraries. Throughout the study, python libraries are used namely Scikit-learn (Pedregosa et al., 2011) and Imbalanced-learn (Lemaître, Nogueira, & Aridas, 2017) for the known methods. Additionally, our code is developed by python to implement the proposed method.

In our implementation, we propose a method which respects the data structure. To understand the data structure the distances between all pairs in the dataset are identified. In our study, we use Density-Based Spatial Clustering of Applications with Noise (DBSCAN) which identifies the density distribution (Ester, Kriegel, Sander, & Xu, 1996; Schubert, Sander, Ester, Kriegel, & Xu, 2017). DBSCAN is applied in a wide variety of fields such as anomaly detection, medical imaging, and video processing (Alhussein & Ali, 2020; Baselice, Coppolino, Antonio, Ferraioli, & Sgaglione, 2015; Bilgin & Çamurcu, 2005; Dokuz, Çelik, & Ecemis, 2020; Huan & Wenhui, 2013; Yaşar & Albayrak). Technical details are given in the following sections. After data topology is identified, synthetically generated data through the Weighted Arithmetic Mean (WAM) approach is used to balance unbalanced yeast data. Thus, the balanced data could be used to train ML algorithms to obtain better performance. The balanced dataset is classified by Random Forest (RF), Support Vector Machine (SVM), Stochastic Gradient Descent (SGD), Neural Network (NN), and AdaBoost (AB) algorithms, and the results are presented. As performance indicators, Accuracy, Area Under ROC curve, Area
Under the Curve, Recall, Precision, F1 Score, Specificity, Sensitivity, Geometric Mean, Arithmetic Mean values are taken into account.

In the following sections, we introduce the dataset for the test case, technical details of the proposed method, brief description of ML algorithms, performance metrics, result and discussion, and conclusion.

1. MATERIALS AND METHOD

1.1. Dataset

In this study, an imbalanced yeast dataset is used from KEEL (Knowledge Extraction based on Evolutionary Learning) opensource software tool site ( ). In this dataset, a total of 1484 instances are recorded, including 89.01% of them are negatives and 10.99% of the dataset is positive. 8 features are available, namely Mcg [0.11, 1.0], Gvh [0.13, 1.0], Alm [0.21, 1.0], Mit [0.0, 1.0], Erl [0.5, 1.0], Pox [0.0, 0.83], Vac [0.0, 0.73], Nuc [0.0, 1.0], Class {positive, negative} (K. Nakai & Kanehisa, 1991; Kenta Nakai & Kanehisa, 1992). The class is positive when the protein is located on the prefered side and negative otherwise. In other words, the positive class represents the yeast is localized at MIT, CYT, ME3, and EXC, and the negative class represents the yeast is localized at ME1, VAC, POX, and ERL. Therefore, the trained ML model predicts the side of the protein for the given values.
The imbalance ratio between the majority and minority classes is 0.12339137 for raw dataset. In this study, the dataset is balanced by removing from majority (negative) class by All KNN (KNN), Cluster Centroids (CC), Condensed Nearest Neighbor (CNN), Edited Nearest Neighbors (ENN), Near Miss (NM), Neighborhood Cleaning Rule (NCR), Random Under Sampler (RUS), Repeated Edited Nearest Neighbors (RENN), and Tomek Links (TL). Also, we proposed a method which resamples the minority class. The minority class is resampled by DBSCAN with Weighted Arithmetic Mean (WAM). In Table 1, the number of elements of minority and majority classes are shown for raw and balanced datasets by the listed methods. Some of the methods are balanced data perfectly such as CC, NM, and RUS. Other methods balanced the dataset at various levels. In the proposed method, WAM, the imbalance ratio is close to be perfect by 1.017411052. Although the balancing approaches provide equal distribution of the dataset, they are prone to change data topology significantly.
Table 1: Raw data and balanced datasets show a reduced imbalance ratio

<table>
<thead>
<tr>
<th>Method</th>
<th>Majority</th>
<th>Minority</th>
<th>Total</th>
<th>Imbalance ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Raw</td>
<td>1321</td>
<td>163</td>
<td>1484</td>
<td>0.12339137</td>
</tr>
<tr>
<td>All KNN</td>
<td>1131</td>
<td>163</td>
<td>1294</td>
<td>0.144120248</td>
</tr>
<tr>
<td>Cluster Centroids</td>
<td>163</td>
<td>163</td>
<td>326</td>
<td>0.761682243</td>
</tr>
<tr>
<td>Condensed Nearest Neighbor</td>
<td>214</td>
<td>163</td>
<td>377</td>
<td>0.140759931</td>
</tr>
<tr>
<td>Edited Nearest Neighbors</td>
<td>1158</td>
<td>163</td>
<td>1321</td>
<td>1</td>
</tr>
<tr>
<td>Near Miss</td>
<td>163</td>
<td>163</td>
<td>326</td>
<td>0.142607174</td>
</tr>
<tr>
<td>Neighborhood Cleaning Rule</td>
<td>1143</td>
<td>163</td>
<td>1306</td>
<td>1.017411052</td>
</tr>
<tr>
<td>Random Under Sampler</td>
<td>163</td>
<td>163</td>
<td>326</td>
<td>1.017411052</td>
</tr>
<tr>
<td>Repeated Edited Nearest Neighbors</td>
<td>1078</td>
<td>163</td>
<td>1241</td>
<td>0.151205937</td>
</tr>
<tr>
<td>Tomek Links</td>
<td>1292</td>
<td>163</td>
<td>1455</td>
<td>0.126160991</td>
</tr>
<tr>
<td>Weighted Arithmetic Mean</td>
<td>1321</td>
<td>1344</td>
<td>2665</td>
<td>1.017411052</td>
</tr>
</tbody>
</table>

1.2. Proposed Method

Additional to known methods, we use mean-based approach to balance the data. The approach starts with identification of the whole data structure and then synthetic data is generated for the closest neighbors. The approach ends with a sufficient number of synthetic data added to the raw dataset.

The close pair of data points are identified by the Euclidian distance. DBSCAN algorithm is utilized to extract the best group of pairs which represent the data structure.

In the algorithm, the closest neighbors around the selected datum are defined with a specified range in the minority class. The specified range is identified brute force method. By using Weighted Arithmetic
Mean (WAM), among the identified pairs, synthetic data is generated to balance the classes. The proposed method follows the listed steps.

The imbalance ratio of the dataset is calculated. If the dataset has considerably unbalanced, further steps are applied.

The considered range is identified by brute force. The range is expanded until the required number of pairs is covered.

If the data points $x$ and $y$ are defined as in formula (1)

$$
x = [x_1, x_2, \ldots, x_n]^T
$$
$$
y = [y_1, y_2, \ldots, y_n]^T
$$

(1)

The Euclidean distance metric is calculated by the formula (2).

$$
d(x, y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}
$$

(2)

The dataset is balanced by means of Weighted Arithmetic Mean (WAM). The WAM for vectors is defined for the data points $x$ and $y$ in equation (3) as follows:

$$
x = [x_1, x_2, \ldots, x_n]^T \in \mathbb{R}^n_+
$$
$$
y = [y_1, y_2, \ldots, y_n]^T \in \mathbb{R}^n_+
$$

(3)
Let $\alpha$ be a random number from $[0,1]$. The equation to generate WAM is given in equation (4).

\[
\begin{bmatrix}
 x_1 (1 - \alpha) + \alpha y_1 \\
 x_2 (1 - \alpha) + \alpha y_2 \\
 \vdots \\
 x_n (1 - \alpha) + \alpha y_n 
\end{bmatrix}
\]

(4)

Lastly, for generating a synthetic sample, we use equation (5)

\[
S_{new} = x \Delta y
\]

(5)

Formula (5) is repeated until the dataset is balanced.

The listed steps are presented in the form of a flowchart in Figure 1.
Figure 1: Algorithm workflow of resampling method by DBSCAN with Weighted Arithmetic Mean
1.3. Utilized Classification Methods

In the study, five different classifiers are used to experiment the performance improvement. Random Forest Algorithm, Support Vector Machine, Stochastic Gradient Descent, Neural Network, and AdaBoost are widely accepted and utilized machine learning algorithms. All the algorithms are known to be supervised machine learning algorithms.

The listed algorithms are trained by 60% of the data, and the rest of the 40% is used for the tests. The analysis is averaged out of 1500 runs of all algorithms to obtain the statistically significant results and to prevent any single error is done by the splitting of the dataset.

1.3.1. Random Forest Algorithm

Random Forest (RF) algorithm is relatively simple and highly efficient. RF is based on the decision trees. The considerable disadvantage of decision trees which is inherently prone to including inconsistency. The inconsistent nature is eradicated by constructing a random forest out of decision trees. Thus, RF classifier makes the final predictions based on several sub classifiers, namely trees. The class that has the most votes is selected as the prediction (Liaw & Wiener, 2002).
1.3.2. Support Vector Machine

Support Vector Machine (SVM) algorithm as an approach that maps the dataset into a high-dimensional hyperspace to find the best separation by optimizing the margin between classes (Vapnik, 2013). The trained algorithm predicts new objects by separating hyperplane (Demidova, Klyueva, Sokolova, Stepanov, & Tyart, 2017).

1.3.3. Stochastic Gradient Descent

Stochastic Gradient Descent (SGD) updates the parameter for every training example $x_i$ and its label $y_i$ (Barani, Savadi, & Yazdi, 2021):

$$\theta = \theta - \eta \nabla_{\theta} J(\theta; x_i; y_i)$$ (6)

It is therefore usually much faster than other gradient descent algorithms such as Batch Gradient Descent. Additionally, the algorithm selects a randomly small portion of the dataset. This approach prevents any performance loss for the data with a high rate of redundancy. The algorithm stops if reaches the specified number of steps or the accuracy threshold.

1.3.4. Neural Network

As the Neural Network algorithm, Multi-layer Perceptron (MLP) classifier is used (Glorot & Bengio, 2010; He, Zhang, Ren, & Sun, 2015; Hinton, 1990; Kingma & Ba, 2014). It is known as a
feedforward artificial neural network. MLP is a supervised algorithm which learns by a function in the following form:

\[
f(\cdot)R^m \rightarrow R^o
\]  

(7)

by training with a dataset, where \( m \) represents the number of variables and \( o \) represents the label. For a given set of variables, \( X = x_1, x_2, ..., x_m \) and label \( y \), it can extract a non-linear function for classification.

1.3.5. AdaBoost

AdaBoost is an ensemble learning method like RF (Drucker, 1997; Freund & Schapire, 1997; Trevor Hastie, Rosset, Zhu, & Zou, 2009). The core methodology of AdaBoost is to train a sequence of weak learners. The weak learners have various weights during the voting. Thus, the voting predictions out all of the weak learners are obtained by combination, so majority vote. The modifications of data at every (so-called boosting) iteration is that algorithm updates the applied weights \( w_1, w_2, ..., w_n \) for the training dataset. Initially, those weights are equal and \( w_i = \frac{1}{N} \) where \( N \) is the number of samples. After every iteration, the weights are individually updated, and the algorithm is applied again to the update weights of the data. By the increasing number of iterations, examples that are difficult to predict gain increasing influence. Thus, each subsequent weak learner is forced to focus on the examples that are missed in the previous iteration (T Hastie, Tibshirani, & Friedman, 2009).
1.4. Model Performance Measurements

To evaluate the performance of machine learning methods, a confusion matrix for binary classification is shown in Table 2. The columns represent the predicted values and the rows represent the actual values. In the specified yeast data, the positive class represents the localization site is MIT, CYT, ME3, and EXC, and the negative class represents ME1, VAC, POX, and ERL.

Table 2: Confusion matrix for a binary classification

<table>
<thead>
<tr>
<th>Actual class</th>
<th>Predicted class</th>
<th>Predicted class</th>
</tr>
</thead>
<tbody>
<tr>
<td>Positive</td>
<td>True Positive, TP</td>
<td>False Negative, FN</td>
</tr>
<tr>
<td>Negative</td>
<td>False Positive, FP</td>
<td>True Negative, TN</td>
</tr>
</tbody>
</table>

A variety of widely accepted performance metrics such as Accuracy, Recall, Precision, Specificity, F1 score, Area Under ROC curve, Area Under the Curve, based on the confusion matrix utilized as the performance indicators (Fatourechi et al., 2008).

Accuracy is defined by the ratio of samples classified correctly to the number of all samples.
The recall is the ratio of samples correctly classified to the total number of positive samples.

\[
Recall = \frac{TP}{TP + FN}
\]  

(9)

Precision is the ratio of samples correctly classified as positive by the total number of samples classified as positive.

\[
Precision = \frac{TP}{TP + FP}
\]

(10)

Specificity is the ratio of samples correctly classified as positive by the total number of samples truly classified as negative and falsely classified as positive.

\[
Specificity = \frac{TP}{TN + FP}
\]

(11)

F1 score is the harmonic mean of Precision and Recall scores.

\[
F1\ score = 2 \times \frac{Precision \times Recall}{Precision + Recall}
\]  

(12)
Area Under ROC curve shows the total area under the Receiver Operating Curve.

The previously mentioned metrics show the average of the measurements for negative and positive. Area Under the Curve is presented separately for 0 and 1.

All the measurements are shown in tabular form and Accuracy is depicted as a graph to compare the ML performances.

Lastly, overall performances are calculated by geometric and arithmetic mean.

2. RESULTS AND DISCUSSIONS

The yeast dataset is used throughout this study. In the study, the machine learning performance increase is aimed by means of DBSCAN combined with the Weighted Arithmetic Mean (WAM) resampling method. The total number of data is 1484. 1321 of them are majority class, 0, and 163 of them are minority class, 1. To minimize the imbalance rate, 0.12339137, and provide a balanced dataset, the minority class is resampled synthetically by the proposed method and 9 other known undersampling methods.

In the specified method, the paired neighbor zone is identified by brute force. In Figure 2, the zone for DBSCAN is expanded, and for the specified zones, a total number of neighbors are given. The sufficient number of neighbors, 1181, is extracted for the radius 18.
Thus, 1181 synthetic samples are generated from the minority class by WAM. After resampling, the total number of minority class is 1344 and majority class is 1321. The imbalance ratio of the resampled dataset is 0.9 which shows a great improvement.

![Graph showing number of pairs vs radius of the zone]

**Figure 2:** The neighboring zone is expanded until the 20-unit length of the radius. For radius 18, 1181 pairs which are the closest to the balance level are identified.

The yeast dataset is depicted by Mcg and Mit attributes in 2D graphs to illustrate distributions of the imbalanced and balanced dataset classes. The raw data and resampled data are shown in **Figure 3** and 4, respectively. As seen in the figures, synthetic data are mostly generated at the dense location.
Figure 3: (Color online) The raw dataset is 1321 majority and 163 minority classes.

Figure 4: (Color online) Resampled data is presented with the raw data. Additional to the raw data, 1181 synthetic data is generated by DBSCAN combined with WAM.

In this work, we used Random Forest (RF), Support Vector Machine (SVM), Stochastic Gradient Descent (SGD), Neural Network (NN), and AdaBoost as the machine learning classifiers. While we compare the balancing methods, we compare the ML methods for the specified
The dataset is randomly split into sections as 60% for training and 40% for test data. All algorithms are repeated 1500 times for all datasets with different training and test sets to prevent any bias because of selection. Lastly, the cumulative averages of performance metrics are presented.

To measure the performance of machine learning algorithms, we have utilized Accuracy, Recall, Precision, F1 Score, Specificity, Sensitivity, Area Under ROC curve, Area Under the Curve. Additionally, we included Geometric Mean, Arithmetic Mean in the measurements to present the overall quality. Lastly, all experiment results are presented in

Table 3,

Table 4,

Table 5,

Table 6, and

Table 7 for RF, SVM, SGD, NN, and AB respectively.

In Table 3, the original data, the synthetically generated data by All KNN, Cluster Centroids, Condensed Nearest Neighbor, Edited Nearest Neighbors, Near Miss, Neighborhood Cleaning Rule, Random Under Sampler, Repeated Edited Nearest Neighbors, Tomek Links, and Weighted Arithmetic Mean) are trained and tested by RF. The
synthetically resampled dataset provides an improvement on performance scores. The proposed method provides the best performances between the listed methods. The Accuracy score of original data increased from 0.9449 to 0.9677; the Area Under ROC curve increased from 0.9646 to 0.9951; the Area Under the Curve 1 increased from 0.7885 to 0.9679; the Recall increased from 0.7885 to 0.9679; the Precision increased from 0.8269 to 0.9680; the F1 score increased from 0.7885 to 0.9677; the Specificity increased from 0.7885 to 0.9679. The overall performance improvements are from 0.7885 to 0.9679 by Geometric Mean and from 0.7761 to 0.8669 by Arithmetic Mean. Only performance loss measurement is for Area Under the Curve 0 (from 0.2115 to 0.0321). This is a known deficit for resampling methods.

Table 3: Performance values of yeast dataset classification results by Random Forest (RF)

<table>
<thead>
<tr>
<th></th>
<th>Accuracy</th>
<th>Area Under ROC curve</th>
<th>Area Under the Curve 0</th>
<th>Area Under the Curve 1</th>
<th>Recall</th>
<th>Precision</th>
<th>F1 Score</th>
<th>Specificity</th>
<th>Sensitivity</th>
<th>Geometric Mean</th>
<th>Arithmetic Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Raw</td>
<td>0.9</td>
<td>0.9</td>
<td>0.2</td>
<td>0.7</td>
<td>0.7</td>
<td>0.8</td>
<td>0.7</td>
<td>0.7</td>
<td>0.7</td>
<td>0.7</td>
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</tr>
<tr>
<td></td>
<td>44</td>
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<td>88</td>
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<td>88</td>
<td>88</td>
<td>88</td>
<td>88</td>
<td>76</td>
</tr>
<tr>
<td>All KNN</td>
<td>0.9</td>
<td>0.9</td>
<td>0.1</td>
<td>0.8</td>
<td>0.8</td>
<td>0.9</td>
<td>0.8</td>
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<td></td>
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<tr>
<td>Condensed Nearest Neighbor</td>
<td>0.8</td>
<td>0.8</td>
<td>0.1</td>
<td>0.8</td>
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<td>0.8</td>
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<td>2</td>
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</tr>
<tr>
<td>Edited Nearest</td>
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<td>0.1</td>
<td>0.8</td>
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<td>0.9</td>
<td>0.8</td>
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<td>7</td>
<td>3</td>
<td>3</td>
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</tr>
</tbody>
</table>
Similarly, all datasets are tested under the same condition by SVM. The results are summarized in Table 4. As shown in the results, the proposed method provides better performance in more metrics (Area Under ROC curve, Area Under the Curve 1, Recall, Precision, F1 score, Specificity) than the other known methods. Therefore, overall quality measurements (Geometric and Arithmetic Mean) show higher performance.

Table 4: Performance Values of Yeast Dataset Classification Results with Support Vector Machine (SVM)
In Table 5, the resampled datasets are trained by SGD. Although the proposed method is providing better performance, Repeated Edited
Nearest Neighbors (RENN) method shows higher quality in some areas such as Accuracy, Area Under ROC curve, and Precision. These metrics are related to estimating positive values which is our interest. Therefore, while SGD is used as the classifier, RENN is a relatively better resampling method. For overall quality measurement, the geometric mean is higher for WAM against all the other methods. Arithmetic mean is very close for RENN (0.6553) and WAM (0.6552).

**Table 5:** Performance Values of Yeast Dataset Classification Results with Stochastic Gradient Descent (SGD)

<table>
<thead>
<tr>
<th>Method</th>
<th>Accuracy</th>
<th>Area Under ROC curve</th>
<th>Area Under the Curve 0</th>
<th>Area Under the Curve 1</th>
<th>Precision</th>
<th>F1 Score</th>
<th>Specificity</th>
<th>Sensitivity</th>
<th>Geometric Mean</th>
<th>Arithmetic Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>All KNN</td>
<td>0.81</td>
<td>0.81</td>
<td>0.43</td>
<td>0.56</td>
<td>0.61</td>
<td>0.53</td>
<td>0.69</td>
<td>0.56</td>
<td>0.65</td>
<td>0.65</td>
</tr>
<tr>
<td>Cluster Centroids</td>
<td>0.57</td>
<td>0.68</td>
<td>0.42</td>
<td>0.57</td>
<td>0.58</td>
<td>0.50</td>
<td>0.57</td>
<td>0.57</td>
<td>0.57</td>
<td>0.57</td>
</tr>
<tr>
<td>Edited Nearest Neighbors</td>
<td>0.82</td>
<td>0.82</td>
<td>0.42</td>
<td>0.57</td>
<td>0.60</td>
<td>0.57</td>
<td>0.60</td>
<td>0.57</td>
<td>0.62</td>
<td>0.62</td>
</tr>
<tr>
<td>Neighborhood Cleaning Rule</td>
<td>0.80</td>
<td>0.79</td>
<td>0.43</td>
<td>0.56</td>
<td>0.61</td>
<td>0.53</td>
<td>0.56</td>
<td>0.56</td>
<td>0.56</td>
<td>0.56</td>
</tr>
<tr>
<td>Near Miss</td>
<td>0.54</td>
<td>0.64</td>
<td>0.45</td>
<td>0.54</td>
<td>0.54</td>
<td>0.46</td>
<td>0.54</td>
<td>0.54</td>
<td>0.54</td>
<td>0.54</td>
</tr>
<tr>
<td>Random Under Sampler</td>
<td>0.60</td>
<td>0.72</td>
<td>0.39</td>
<td>0.60</td>
<td>0.62</td>
<td>0.55</td>
<td>0.60</td>
<td>0.60</td>
<td>0.60</td>
<td>0.60</td>
</tr>
<tr>
<td>Repeated Edited Nearest Neighbors</td>
<td>0.82</td>
<td>0.88</td>
<td>0.37</td>
<td>0.62</td>
<td>0.62</td>
<td>0.71</td>
<td>0.60</td>
<td>0.62</td>
<td>0.62</td>
<td>0.62</td>
</tr>
</tbody>
</table>
In Table 6, the datasets are trained and clustered by NN. The performance metric shows that WAM is the best in 5 metrics, RENN is the best in 3 metrics, and Condensed Nearest Neighbor (CNN) is the best in 1 metric. CNN provides performance improvement for Area Under the Curve 0 which is expected to be damaged after resampling, so it is an irrelevant improvement for this study. The same is true for Tomek Links. Therefore, we could conclude NN shows the best results with RENN and WAM. Between these methods, WAM is better in more metrics and overall metrics.

**Table 6:** Performance Values of Yeast Dataset Classification Results with Neural Network (NN)
In Table 7, the datasets are classified with AB algorithms. AB shows better performance with WAM. In the performance metrics, Area Under ROC curve shows better performance for Cluster Centroids (0.9970) than WAM (0.9932). Additionally, in the overall metrics, WAM provides better performance (0.9700 for Geometric and 0.8681 for Arithmetic mean) than all the other listed methods.
Table 7: Performance Values of Yeast Dataset Classification Results with AdaBoost (AB)

<table>
<thead>
<tr>
<th>Method</th>
<th>Accuracy</th>
<th>Area Under ROC curve 0</th>
<th>Area Under ROC curve 1</th>
<th>Area Under the Curve 0</th>
<th>Area Under the Curve 1</th>
<th>Recall</th>
<th>Precision</th>
<th>F1 Score</th>
<th>Specificity</th>
<th>Sensitivity</th>
<th>Geometric Mean</th>
<th>Arithmetic Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Raw</td>
<td>0.9</td>
<td>0.9</td>
<td>0.1</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.7</td>
</tr>
<tr>
<td>All</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
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</tr>
<tr>
<td>KNN</td>
<td>1</td>
<td>5</td>
<td>6</td>
<td>4</td>
<td>4</td>
<td>7</td>
<td>1</td>
<td>6</td>
<td>6</td>
<td>6</td>
<td>6</td>
<td>6</td>
</tr>
<tr>
<td>ClusterCentroids</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.8</td>
</tr>
<tr>
<td>NearestNeighbors</td>
<td>0.8</td>
<td>0.8</td>
<td>0.1</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.7</td>
</tr>
<tr>
<td>EditedNearestNeighbors</td>
<td>0.9</td>
<td>0.9</td>
<td>0.1</td>
<td>0.8</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
</tr>
<tr>
<td>Neighbors</td>
<td>54</td>
<td>77</td>
<td>87</td>
<td>91</td>
<td>91</td>
<td>91</td>
<td>1</td>
<td>91</td>
<td>91</td>
<td>91</td>
<td>91</td>
<td>24</td>
</tr>
<tr>
<td>NeighborhoodClean</td>
<td>0.8</td>
<td>0.8</td>
<td>0.1</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.7</td>
</tr>
<tr>
<td>NeighborhoodRule</td>
<td>0.9</td>
<td>0.9</td>
<td>0.0</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.8</td>
</tr>
<tr>
<td>Random</td>
<td>0.8</td>
<td>0.9</td>
<td>0.1</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
</tr>
<tr>
<td>Method</td>
<td>Accuracy</td>
<td>Area Under ROC curve</td>
<td>Area Under the Curve 0</td>
<td>Area Under the Curve 1</td>
<td>Recall</td>
<td>Precision</td>
<td>F1 Score</td>
<td>Specificity</td>
<td>Sensitivity</td>
<td>Geometric Mean</td>
<td>Arithmetic Mean</td>
<td></td>
</tr>
<tr>
<td>--------------------------------</td>
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<td>-------------</td>
<td>----------------</td>
<td>-----------------</td>
<td></td>
</tr>
<tr>
<td>Under Sampler</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Repeat Edited Nearest Neighbors</td>
<td>0.9</td>
<td>0.9</td>
<td>0.0</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.8</td>
<td></td>
</tr>
<tr>
<td>Tomek Links</td>
<td>0.9</td>
<td>0.9</td>
<td>0.1</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td></td>
</tr>
<tr>
<td>Weighted Arithmetic Mean</td>
<td>0.9</td>
<td>0.9</td>
<td>0.0</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.8</td>
<td></td>
</tr>
</tbody>
</table>

In summary, a resampling minority group of the dataset led to better performance measurements. The proposed sampling method is provided better ML classification, especially for RF. Additionally, the comparison of listed algorithms’ accuracy performances is shown in Figure 5. The ML algorithms perform uncorrelated with the resampling method. SGD has the lowest performance for this particular dataset. On the other hand, RF and AB which have similar training methodology, are the best performers. Lastly, Raw, All KNN, Edited Nearest Neighbors, Neighborhood Cleaning Rule, Repeated Edited Nearest Neighbors, Tomek Links, and Weighted Arithmetic
Mean perform relatively better than Cluster Centroids, Condensed Nearest Neighbor, Near Miss, Random Under Sampler.

Figure 5: Accuracy performances of machine learning algorithms for the datasets

3. CONCLUSIONS

An imbalanced dataset is synthetically resampled to reduce or remove the imbalance ratio. The resampling method uses a combination of Euclidean distance metric, DBSCAN, and Weighted Arithmetic Mean (WAM). The findings are compared with 9 undersampling methods such as All KNN (KNN), Cluster Centroids (CC), Condensed Nearest Neighbor (CNN), Edited Nearest Neighbors (ENN), Near Miss (NM), Neighborhood Cleaning Rule (NCR), Random Under Sampler (RUS),
Repeated Edited Nearest Neighbors (RENN), and Tomek Links (TL). 5 different machine learning algorithms, namely Random Forest (RF), Support Vector Machine (SVM), Stochastic Gradient Descent (SGD), Neural Network (NN), and AdaBoost (AB), are used to cluster the datasets. Accuracy, Recall, Precision, Specificity, Sensitivity, F1 score, Area Under ROC curve, Area Under the Curve are used as performance metrics. The performance measurements show the resampling method has better performance than the listed methods. The lowest and highest values of performance metric as follows:

- **Accuracy** is the lowest, 0.5174, for CNN and SGD and the highest, 0.9700, for WAM and AB
- **Precision** is the lowest, 0.4230, for CNN and SGD and the highest, 0.9700 for WAM and AB
- **Recall** is the lowest, 0.5000, for Raw and SVM and the highest, 0.9700 for WAM and AB
- **F1 Score** is the lowest, 0.4655, for NN and SGD and the highest, 0.9700 for WAM and AB
- **Specificity** is the lowest, 0.5000, for Raw and SVM and the highest, 0.9700 for WAM and AB
- **Sensitivity** is the lowest, 0.5000, for Raw and SVM and the highest, 0.9700 for WAM and AB
- **Area Under ROC curve** is the lowest, 0.5763, for CNN and SGD and the highest, 0.9970 for CC and AB

As seen in the classification metrics, resampling method provides better performance.
Moreover, the classifier performances are compared by means of accuracy. RF and AB have better performers, on the other hand, SGD has relatively lower accuracy performance.

In summary, the experimental results show that the resampled dataset is more successful than the raw dataset and the listed undersampling methods, and AB is best classifier for the resampling method.

**Acknowledgments**

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**Authors' Contribution**

The author completed the study with his effort.

**The Declaration of Conflict of Interest/ Common Interest**

No conflict of interest or common interest has been declared by the authors.

**The Declaration of Publishing Ethics**

This study is done by research and publication ethics.
REFERENCES

Retrieved from https://sci2s.ugr.es/keel/dataset/data/classification/


CHAPTER 7

NUMERICAL EVALUATION OF EXPERIMENTAL RESULTS FOR BURIED PIPES IN GEOSYNTHETIC REINFORCED SAND

Res. Assist. Dr. Güneş BABAGİRAY

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INTRODUCTION

Underground systems such as pipelines under various loads are important for civilization in transporting many materials from one place to another. Some improvement ways are required to take advantage of piping systems and avoid economic and safety issues.

In recent years, there are some studies in geotechnical field related to underground studies. In these studies, highly demanded geosynthetic materials are used.

This study was made to investigate the protection capacity of three types of geosynthetics by numerical studies. Geocell (Yang, Han, Parsons, & Leshchinsky, 2010; Hedge & Sitraham, 2015; Biabani, Indraratna, & Ngo, 2016), geogrid (Laman & Yıldız, 2007; Sawwaf, 2007; Ghazavi & Lavasan, 2008; Latha & Somwanshi, 2009; Kim & Lee, 2013), geotextile (Palmeira & Andrade, 2010; Tupa & Palmeira, 2007) and combinations of these geosynthetics above pipelines were modelled.

Physical experiments (Babagiray, 2017) and numerical modelings (Laman & Yıldız, 2007; Sawwaf, 2007; Ghazavi & Lavasan, 2008; Latha & Somwanshi, 2009; Yang et al., 2010; Hedge & Sitraham, 2015; Kim & Lee, 2013; Biabani et al., 2016) are proper ways to gain better understanding of buried pipeline behavior.

The experiments are required lots of variables such as types of protective materials; their uses and depths; pipe types; soil types; transmitted materials etc. All these things are limited by material
obtaining and time constraints. Because of that reason numerical methods applied to this kind of engineering problems, have great importance. By this way the optimum design for each required alternative can be obtained by using a three-dimensional finite element. For this reason, the finite element results should be verified with the experimental results.

In this study, the results of the finite element models were validated by using the test results performed by Babagiray (2017). Realistic Modeling and Simulation of Earthquakes, and/or Soils, and/or Structures and their Interaction Simulator (Real ESSI) software, was used to investigate the displacements on buried pipelines with and without geosynthetic protective layers. For this software which works with coding language, terminal (there are some alternative names for the terminal like as, console, shell, command line, command prompt) was used in Linux. Linux is similar to other operating systems, such as Windows, OS X, or iOS. Terminal is an interface in which text based on commands can be typed and executed. It can be much faster to complete some tasks using a terminal than graphical applications and menus. Another benefit is allowing access to many more commands and scripts. By means of commands that can be written in the terminal window, geometry, element identification, material information, analysis etc. were created for the model. Some programs such as Gmsh (a three-dimensional finite element mesh generator with built-in pre- and post-processing facilities) (Geuzaine & Remacle, 2009) and Paraview (an open-source,
multi-platform data analysis and visualization application) (Ahrens, Geveci, & Law, 2005) were used to make scripting fast and easy.

1. REAL ESSI SIMULATOR

The Real ESSI Simulator (also known as The MS-ESSI Simulator), is a software, hardware and documentation system for high (or any selected level of) fidelity, high performance, time domain, nonlinear/inelastic, deterministic or probabilistic, 1 Dimension (D), 2D or 3D, finite element modeling and simulation of statics and dynamics of soil, statics and dynamics of rock, statics and dynamics of structures, statics of soil-structure systems, and dynamics of earthquake-soil-structure system interaction. The Real ESSI Simulator allows modeling of a full hierarchy of models, from simplest models to the very sophisticated models. The system is used for the design and assessment of static and dynamic behavior of infrastructure objects, including buildings, bridges, dams, nuclear installations, tunnels, etc. (Real ESSI, 2018).

1.1. Domain Specific Language

The Real ESSI language provides modularity through the include directive/command, and user functions. This allows complex analysis cases to be parameterized into modules and functions which can be reused in other models. Finite element analysis (FEA) is unitless, that is, all calculations are carried out without referencing a particular unit system. This leaves the task of unit correctness up to the user of FEA analysis. This represents a recurring source of error in FEA analysis. Physical unit safety is enforced in Real ESSI by implementing all base
variables as physical quantities, that is, all variables have a unit associated with it. Command calls are sensitive to units. For example, the node creation command call expects the node coordinates to be input with the corresponding units. This approach to FEA with unit awareness provides an additional layer of security to FEA calculations, and forces the user to carefully think about units. This can help catch some common mistakes (Abell, Feng, Yang, Wang, & Jeremic, 2018b).

Finally, an emphasis is placed on model verification and validation. To this end, Real ESSI provides an interactive programming environment with all the ESSI syntax available. By using this environment, the user can develop tests to detect errors in the model that are not programming errors. For example, the user can query nodes and elements to see if they are set to appropriate states. Also, several standard tools are provided to check element validity (Abell et al., 2018b).

1.2. Variables, Basic Units and Modelling

ESSI works with coding that commands given in the background of the model can be seen so the terminal provides ease of the using ESSI. When starting with the terminal window, for opening a file; the user should type `essi` to get to the ESSI prompt and start Real ESSI in interactive mode then input command manually.

It is assumed that vertical axes is global Z axes. The assignment (=) operator is used for defining variables and mathematical operations (addition, subtraction, multiplication, division, modulus). Each
command line has to end with a semicolon (;). The syntax ignores extra white spaces, tabulations and newlines. Comment on a line begins with either "/" or "/!" and last until the end of current line. Internally, all units are represented in the base SI units (m-s-kg). A list of command line options is available by calling essi from the command line as essi -h, like seen as in Figure 1.

![Figure 1: A List of Commands Options](image)

All models have to be named: model name "model_name_string". This is important as output files are named based on model name. Material properties as mass density, elastic modulus, poisson ratio etc. should be defined for each material. Depending on material model, there will be additional material parameters. To exit ESSI, `bye;` must be typed at the prompt. If `bye;` command is included at the end of a script, the essi program will exit upon execution of the script regardless of any errors which occur during execution (Abell et al., 2018b).

2. BUILDING FILES WITH FILE EXTENSION OF .GEO AND .MSH IN GMSH

The first step is to make the geometry file in Gmsh. While creating the geometry the user should also define all the physical groups on which they intend to either apply boundary condition, define elements etc.
Physical groups can be created of type {nodes, lines, surface or volume} containing one or more geometrical entities of their respective type. Their only purpose is to assemble elementary entities into larger groups, possibly modifying their orientation, so that they can be referred to by the mesh module as single entities. Also physical groups of the surface as fixities is created (Sinha et al., 2018). Geometrical entities are the most elementary group in Gmsh. Each point, line, surface and volume is a geometrical entity and possess a unique identification number (id). Elementary geometrical entities can then be manipulated in various ways, for example using the Translate, Rotate, Scale or Symmetry commands. They can be deleted with the Delete command, provided that no higher-dimension entity references them (Sinha, Feng, Wang, & Jeremic, 2018).

2.1. Modelling of the System

High density polyethylene (HDPE) pipe systems with and without protective geosynthetic layers and the datas obtained in Babagiray (2017) were used in modeling. The sand reinforced with a geocell, geogrid or geotextile layer and the combination of two of them were examined. For all tests, geosynthetics were placed on 120 mm from surface of the tank. The pipe placed on 50 mm above from the bottom of the tank (Figure 2).

Test tank of size 1000 mm length, 500 mm width and 400 mm height was modeled for the numerical investigation. Well-graded sand with dry density 1613 kg/m³, poisson ratio 0.3, friction angle 36°, elastic modulus 23 MPa. The pipe with density 0.950 g/cm³, poisson ratio
0.4, inner diameter 160 mm, elastic modulus 950 MPa, thickness 10 mm were used in the study. The properties of geosynthetics were given by the manufacturer (Geoplas, 2017).

A hardening soil model von Mises, Armstrong-Frederick was selected for the nonlinear response of sand material. For geosynthetics and the pipe, linear elastic material model was used. 10 steps were used in analyses and time increment is chosen as 0.0060 s like in the experiments. The boundaries of the mesh of models are same as the tank used in experiments. The surfaces were fixed for creating the 3D tank volume. The boundary of the bottom was restricted in all directions. For lateral sides of soil tank boundaries were restricted only in horizontal directions. After creating geometry of model and physical groups, according to element order 2, 27 node element was used.

Figure 2: Cross-Sectional General View of the Tests (Babagiray, 2017)
In the experiments, load was applied to specimens by using a 100 x 100 x 15 mm square steel plate located on the soil layer surface at the distance of 610 mm from front face of the tank. Because of that, load was applied on the nodes of the plate area in the model.

### 2.1.1. Modelling of Reference Test

A sublime text file was used for coding while model drawings with Gmsh. 1/4 of the system was used to start the modeling due to symmetry. The pipe with thickness \( t \) and radius \( r \), soil surrounding the pipe, and contact surface are shown clearly in the Figure 3.

![Figure 3: First Modeled Quarter of System](image)

It is necessary to identify the materials as physically after defining surfaces. For meshing, mesh sizes of each line was determined by Transfinite command. For instance, #16 and #17 lines (Figure 3) were divided into ‘r/meshsize’ parts. \( r \) is the inner radius of pipe and meshsize is a chosen value for dividing lines into parts for meshing more quadratic. Then, the model was symmetrised and rotated for obtaining the next image (Figure 4).
For interface/contact between pipe-soil and geosynthetics-soil, stress based soft contact was used (Abell et al., 2018c). After generating the model, the system was seen in Figure 5.
2.1.2. Modelling System with a Protection Layer of Geocell

Geocells have a three-dimensional cellular structure, which can be used to stabilize foundations by increasing bearing capacity and reducing settlements. Numerical simulations of the geocells are not so easy due to its complex 3D honeycomb structure. The shape of the geocell was modeled with a rectangular shape (Figure 6) as opposed to the actual pseudo-sinusoidal shape that was used in the tests. This prevented meshing issues that could occur due to the complex nature of the mesh under 3D configurations (Yang et al., 2010; Leshchinsky & Ling, 2013; Hegde & Sitharam, 2015). The properties of geocell as specified by the manufacturer are given in Table 1.

Table 1. Properties of the Geocell (Geoplas, 2017).

<table>
<thead>
<tr>
<th>Property</th>
<th>Unit</th>
<th>Geocell</th>
</tr>
</thead>
<tbody>
<tr>
<td>Density</td>
<td>gr/ cm³</td>
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</tr>
<tr>
<td>Carbon black</td>
<td>%</td>
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</tr>
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<td>Tensile strength</td>
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</tr>
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<td>300</td>
</tr>
<tr>
<td>Cell width</td>
<td>mm</td>
<td>250</td>
</tr>
<tr>
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<tr>
<td>Thickness</td>
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<td>1.0</td>
</tr>
<tr>
<td>Cell height</td>
<td>mm</td>
<td>50</td>
</tr>
</tbody>
</table>

After physical volumes of materials, boundary conditions and contact surfaces were defined, model was ready for run and mesh. Geocell mesh size and soil mesh size must be matched each other in geocell-soil composite part.
2.1.3. Modelling of Geogrid Protection Layered Test

The properties of geogrid as specified by the manufacturer are given in Table 2. Figure 7 shows the 3D view of the geogrid layered test.

Table 2. Properties of the Geogrid (Geoplas, 2017).

<table>
<thead>
<tr>
<th>Property</th>
<th>Unit</th>
<th>Geogrid</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unit weight</td>
<td>g/m²</td>
<td>240</td>
</tr>
<tr>
<td>Tensile strength</td>
<td>kN/m</td>
<td>&gt;30</td>
</tr>
<tr>
<td>Elongation at maximum load</td>
<td>%</td>
<td>&lt;8/&lt;8</td>
</tr>
<tr>
<td>Tensile strength at 2% elongation</td>
<td>kN/m</td>
<td>12/12</td>
</tr>
<tr>
<td>Tensile strength at 5% elongation</td>
<td>kN/m</td>
<td>24/24</td>
</tr>
<tr>
<td>Aperture size</td>
<td>mm x mm</td>
<td>40x40</td>
</tr>
<tr>
<td>Sheet width</td>
<td>mm</td>
<td>10</td>
</tr>
<tr>
<td>Thickness</td>
<td>mm</td>
<td>2</td>
</tr>
<tr>
<td>Elastic modulus</td>
<td>MPa</td>
<td>380</td>
</tr>
</tbody>
</table>
2.1.4. Modelling of Geotextile Protection Layered Test

The properties of geotextile as specified by the manufacturer are given in Table 3. Figure 8 shows the 3D view of the geotextile layered test.

Table 3. Properties of the Geotextile (Geoplas, 2017).

<table>
<thead>
<tr>
<th>Property</th>
<th>Unit</th>
<th>Geotextile</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unit weight</td>
<td>g/m²</td>
<td>500</td>
</tr>
<tr>
<td>Thickness</td>
<td>mm</td>
<td>4</td>
</tr>
<tr>
<td>Rupture strength</td>
<td>kN/m</td>
<td>27-29</td>
</tr>
<tr>
<td>Elongation at rupture</td>
<td>%</td>
<td>50-80</td>
</tr>
<tr>
<td>Static puncture strength</td>
<td>N</td>
<td>5500</td>
</tr>
<tr>
<td>Dynamic puncture strength</td>
<td>mm</td>
<td>3</td>
</tr>
<tr>
<td>Aperture size</td>
<td>mm</td>
<td>0.1</td>
</tr>
<tr>
<td>Elastic modulus</td>
<td>MPa</td>
<td>570</td>
</tr>
</tbody>
</table>
2.1.5. Modelling of the Combination of Geogrid & Geocell Protection Layered Test

Figure 9 shows the 3D view of the combination of geogrid and geocell layered test.
2.1.6. Modelling of the Combination of Geotextile & Geocell ProtectionLayered Test

Figure 10 shows the 3D view of the combination of geotextile and geocell layered test.

Figure 10: 3D View of the Combination of Geotextile & Geocell Test in Gmsh.

2.1.7. Modelling of the Combination of Geotextile & Geogrid Protection Layered Test

Figure 11 shows the 3D view of the combination of geotextile and geogrid layered test.
3. gmESSI

After the name of the physical group along with their corresponding elements and nodes gets transferred to the mesh file in Gmsh, all the geometrical entities have a tag list which contains the ids of the physical groups to which it belongs in generated mesh file. An example of meshed front view of the model is seen in Figure 12.
A translator called gmESSI converts the mesh file from Gmsh to Real ESSI Simulator. The primary aim of this program is to provide an easy, handy and powerful pre-processing tool to develop finite element (FE) models in Gmsh and make them interface with various ESSI functionalities. The gmESSI translator package contains the translator, sublime plugin and the manual. The input language for the translator is hybrid i.e. it accepts both Python as well as gmESSI commands. This feature enhances its power beyond translation (Sinha et al., 2018).

The translator utilizes the physical and entity group concept of Gmsh, which gets imprinted in the mesh “.msh” file. The translator then
manipulates these groups to convert the whole mesh to ESSI commands. Thus, making physical groups is the essential, key for conversion. The translator basically provides some strict syntax for naming these physical groups which provides gmESSI information about the elements (or nodes) on which the translation operates. gmESSI can be invoked from the terminal by typing gmessy. Running gmESSI requires, the .gmessi input file and the Gmsh mesh file (.msh) containing physical groups (Sinha et al., 2018).

gmESSI utilizes the mesh (.msh) file to get the respective physical group and translated it to ESSI input (.fei) files. For this a new folder must be created which name as filename.gmessi. The first command in .gmessi file should be to load the mesh file (.msh). The gmESSI translator adds all the nodes from mesh file to ESSI input files. gmESSI translates the gmESSI commands operated on mesh (.msh) file to different ESSI input (geometry, load and analysis) (.fei) files and put them in user-defined directory. Geometry file (geometry.fei) is one part of Real ESSI input file that contains the translation of commands related to only initialization of nodes and elements of the FEM mesh. Load file (load.fei) contains the translation of commands related to the load and boundary conditions on the structure, like declaration of fixities, boundary conditions, master-slave, nodal loads, surface loads etc. Analysis file (main.fei) is the main file which is run on Real ESSI Simulator. The main file must include load, node and element file through include ‘filename.fei’ command (Sinha et al., 2018).
After conversion the mesh file from Gmsh to Real ESSI, terminal window has an appearance as in Figure 13.

The arguments of gmESSI commands can also have tags associated with them so that it becomes easy for the user to interpret the argument and make changes in future. The tag and the argument is separated by `:=`. `Found!!` is a message as shown above on translation log in the terminal means that, the corresponding command was found in the gmESSI command library. `Successfully Converted`, as the
message itself describes, it occurs if the command has been successfully translated.

4. RUNNING REAL ESSI

Real ESSI Simulator outputs total displacements at all the nodes, as well total stress, total strain and total plastic strain at all points of the element in each time step of each stage of loading (Abell et al., 2018b).

After taking a folder as ‘ESSI_Simulation’ which consists of geometry.fei, load.fei, main.fei documents, their name can be added the command line of analysis.fei file, then materials, selfweight of system, etc. could be defined. With all files ready in their place, the next step is to run the analysis.fei file directly in ESSI.

All output from ESSI simulator is stored inside a database format, specifically designed for handling scientific array-oriented data, called HDF5 (Group). HDF stands for ‘Hierarchical Data Format’ and is a self-describing data format suitable for portable sharing of scientific data. The format is created and is maintained by the HDF group (http://www.hdfgroup.org/). Data is stored within the file using a hierarchy similar to a unix filesystem, with groups to store related data and the actual data stored in so-called ‘datasets’ within each group. On running any simulation on Real ESSI simulator output files are produced for each analysis stage (Abell et al., 2018a).
“check model” is the command for checking the boundary on HDF5 before the simulation. Additionally, an output HDF5 file is produced that can be used to display the mesh and do further visual inspections of the model. This file will have initial conditions as outputs for element and nodes (Abell et al., 2018b). This will iterate over domain components (nodes, elements, loads, constraints, etc.) and execute the check model function. Each domain component writes to the terminal if it has encountered an error which gets recorded in essi.log file as well.

“$mpirun -np 10 essi.parallel -f filename_analysis.fei” is the command of start the running. The number ‘10’ means output results at intervals of 10 time steps. Therefore, “filename_analysis.fei” file was run with parallel solver. There are two type of solvers: sequential solver and parallel solver. For sequential runs, a single output file is produced per analysis stage. The files are named according to model and stage names, not by the filename that runs the analysis. In parallel each of the slave process outputs contains all the data corresponding to only the slave process. This is done to make the visualization and output process efficient (Abell et al., 2018a).

The parallel run type was choosen for the model because it provides faster usage than sequential. Steps number of simulation was 50 and load increment was 0.02. This means solving each 50 unit steps, as increasing 0.02 sensitivity.
Running ESSI creates .feioutput file which can be visualized in ParaView using pvESSI plugin. Real ESSI .feioutput file stores all the results in standard units.

5. VISUALIZATION IN PARAVIEW

ParaView package is a powerful multi-platform data analysis and visualization application available as an open source. It can be run on supercomputers to analyze datasets of peta-scale size as well as on laptops for smaller data. pvESSI is a plugin for ParaView that integrates Real ESSI Simulator output to ParaView for visualization. It reads ESSI (HDF5) .feioutput file (Abell et al., 2018c).

pvESSI takes Real ESSI HDF5 output (.feioutput) file format as input and creates a pvESSI folder inside the HDF5 file. pvESSI does this to ensure the visualization to be optimized. The contents inside this folder are not important for any regular user (Abell et al., 2018c). The plug-ins first creates this folder and then uses the content of this folder for visualization in ParaView. Figure 14 shows the visualization of HDF5 output produced of the reference model in ParaView.
6. RESEARCH RESULTS

The results described with each test model are given below:

6.1. Result of Reference Test

In the reference experiment, the displacement value on the midpoint of the pipe was 5.10 mm and it was 4.52 mm in numerical analysis by Real ESSI. Figure 15 shows the displacement view of the reference test.
6.2. Result of Geocell Protection Layered Test

In the geocell protection layered experiment, displacement value on the midpoint of the pipe was 2.11 mm and it was 1.94 mm in numerical analysis by Real ESSI. Figure 16 shows the displacement view of the geocell protection layered test.
6.3. Result of Geogrid Protection Layered Test

In the geogrid layered experiment, displacement value on the pipe was 0.58 mm and it was 0.56 mm in numerical analysis by Real ESSI. Figure 17 shows the displacement view of the geogrid protection layered test.
6.4. Result of Geotextile Protection Layered Test

In the geotextile protection layered experiment, displacement value on the pipe was 0.56 mm and it was 0.53 mm in numerical analysis by Real ESSI. Figure 18 shows the displacement view of the geotextile protection layered test.
6.5. Result of Combination of Geogrid & Geocell Protection Layered Test

In the geogrid&geocell layered experiment, displacement value on the pipe was 0.33 mm and it was 0.28 mm in numerical analysis by Real ESSI. Figure 19 shows the displacement view of the combination system of geogrid & geocell layers.
6.6. Result of Combination of Geotextile & Geocell Protection Layered Test

In the geotextile&geocell layered experiment, displacement value on the pipe was 0.29 mm and it was 0.30 mm in numerical analysis by Real ESSI. Figure 20 shows the displacement view of the combination system of geotextile & geocell layers.
6.7. Result of Combination of Geotextile & Geogrid Protection Layered Test

In the geotextile & geogrid layered experiment, displacement value on the pipe was 0.27 mm and it was 0.21 mm in numerical analysis by Real ESSI. Figure 21 shows the displacement view of the combination system of geotextile & geogrid layers.
The displacement results both experiments and numerical analyses were compared in Table 4. The most successful performance for reducing displacement values was obtained from combination of geotextile&geogrid both in experimental and numerical studies.

**Table 4.** Results of Experiments vs. Numerical Analyses.

<table>
<thead>
<tr>
<th>Name of the System</th>
<th>Displacement (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Experiment (Babagiray, 2017)</td>
</tr>
<tr>
<td>Reference (without geosynthetic)</td>
<td>5.10</td>
</tr>
<tr>
<td>Geocell</td>
<td>2.11</td>
</tr>
<tr>
<td>Geogrid</td>
<td>0.58</td>
</tr>
<tr>
<td>Geotextile</td>
<td>0.56</td>
</tr>
<tr>
<td>Geogrid &amp; Geocell</td>
<td>0.33</td>
</tr>
<tr>
<td>Geotextile &amp; Geocell</td>
<td>0.29</td>
</tr>
<tr>
<td>Geotextile &amp; Geogrid</td>
<td>0.27</td>
</tr>
</tbody>
</table>
CONCLUSION

- Gmsh mesh generator was used to created a model. gmESSI translator was used to convert the mesh file from Gmsh to Real ESSI Simulator.
- For geosynthetics and pipe, a linear elastic material model was used. Hardening soil model von Mises, Armstrong-Frederick was selected for the nonlinear response.
- It was observed that all of the geosynthetic protective systems contributed significantly to the pipe safety.
- FEA results of Real ESSI were consistent with the test results. The most successful performance for reducing displacement values was obtained from combination of geotextile & geogrid.
- Real ESSI can be used for being guide all engineers and producers without doing any experiments.

Acknowledgements

This research was funded by The Scientific and Technical Research Council of Turkey (TUBITAK-2219).

The software called ESSI, which models static and dynamic behavior of the soil by using the finite element method, has developed by Prof. Boris Jeremic and his research team. Thus, special thanks to Prof. Boris Jeremic, Dr. Hexiang Wang, Dr. Han Yang, and Dr. Fangbo Wang for information providing in this research.

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2 A part of this work was published in Babagiray & Jeremic (2019).
REFERENCES


CHAPTER 8

USE OF EXHAUST VALVE PHASE SHIFT METHOD FOR ACCELERATED EXHAUST AFTER-TREATMENT HEAT-UP IN HEAVY-DUTY DIESEL VEHICLES

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INTRODUCTION

Modern on-road automotive vehicles are faced with highly stringent emission regulations. Environmental Protection Agency (EPA) and European Union (EU) demand considerably low Nitrogen Oxide (NO\textsubscript{x}) and Particulate Matter (PM) emission rates for diesel automotive vehicles during both inner-city transport and highway cruise conditions [Dieselnet (2021), EPA (2021)]. There is an ongoing work on diesel engines to limit the harmful engine-out emission rates through renewable fuels, advanced combustion techniques and exhaust gas recirculation [Kozina & Nizetic (2020), Rahman et al. (2021), Gren et al. (2021)].

One way to reduce emission rates is to utilize exhaust after-treatment (EAT) systems at the end of exhaust units on diesel engine systems. Currently, almost all automotive and marine vehicles are equipped with EAT systems to meet the strict emission norms issued by environmental authorities [Alkemade & Schumann (2006)]. Those systems generally include 3 main parts: Diesel Oxidation Catalyst (DOC), Diesel Particulate Filter (DPF) and Selective Catalytic Reduction (SCR). DOC is placed on the system to reduce the unburned hydrocarbons (UHCs) and carbon monoxide (CO). DPF is used to reduce the PM emission rates and SCR is utilized to curb NO\textsubscript{x} emission rates [Reşitoğlu (2015)]. Those additional components in exhaust systems of diesel vehicles are highly effective to decrease tailpipe emission rates, however, they noticeably rely on temperature and mostly operate effectively above 250\degree C [Blakeman et al. (2003),]
Guan et al. (2014), Song et al. (2013)]. This is a serious disadvantage considering vehicles need to spend a significant of time during low loads when exhaust temperatures remain below $250^\circ C$ [Boriboonsomsin (2018)]. Diesel exhaust temperatures need to be enhanced at those light-loaded cases in order to maintain effective EAT and thus, low tailpipe emission rates [Gao et al. (2019)].

Researchers generally attempt to rise exhaust temperatures through either engine-dependent or engine-independent techniques [Honardar et al. (2011)]. One current engine-dependent method for improved exhaust thermal management is to use late fuel injection (LFI) on diesel engine systems [Stadlbauer (2013), Ozel (2018)]. LFI generally achieves moderate rise on exhaust temperature, however, it causes more than $10\%$ fuel consumption penalty which can be regarded as a significant disadvantage [Tan et al. (2020)]. Another effective method is to implement early exhaust valve opening (EEVO) through modulating cam mechanisms [Roberts et al. (2015)]. EEVO allows up to $50^\circ C$ hotter engine-out gas to flow through the EAT system. However, it needs almost $15\%$ extra fuel injection due to the dramatic reduction on closed cycle efficiency [Basaran (2020)]. Unlike EEVO, late intake valve closure (LIVC) – a different cam-based method – can boost exhaust temperature up to $55^\circ C$ at low loads without causing fuel consumption penalty [Garg et al. (2016), Piano et al. (2017)]. But it results in a noticeable volumetric efficiency reduction which considerably decreases exhaust flow rate and thus, affects EAT warm-up negatively [Basaran & Ozsoysal (2017)]. Although LIVC
deteriorates get-warm process, it is highly practical for stay-warm process as it does not need additional fuel injection [Basaran (2021)].

Unlike aforementioned engine-dependent methods, engine-independent techniques are examined to rise exhaust temperatures at low loads as well. One of those strategies is to utilize electrical heating on vehicles [Culbertson (2015)]. Electrical heating is highly effective as it directly heats the EAT system rather than heating the diesel exhaust unit. However, this method requires an external component to be mounted on the engine system which is generally cost-ineffective [Pfahl (2012)]. Other engine-independent strategies are utilizing heat storage units and after-burner devices [Ma (1992), Gumus (2009)]. Those systems are useful to elevate exhaust temperatures. However, similar to electrical heating, they need extra energy and additional units to be placed on the system and thus, production costs are increased.

The objective of this work is to show that utilizing exhaust valve phase shift (EVPS) can be a practical and more fuel-saving approach to improve diesel EAT systems compared to those aforementioned conventional strategies. EVPS does not require any extra unit to be placed on the engine system and causes moderate fuel-inefficiency. Thus, it can be considered as a feasible way to improve EAT effectiveness at low loads.

1. METHODOLOGY

This study considers the implementation of EVPS on a heavy-duty diesel engine system with the aim of improving exhaust temperature.
At first, the properties of the diesel engine used in the study are given. Then, the model is introduced and the formulations it uses are presented. Finally, it is explained how EVPS method is applied on the model to achieve high exhaust temperature in the system.

1.1. Diesel Engine Specifications and Model

The diesel engine selected for analysis is a heavy-duty type which is widely utilized at commercial trucks, public buses and some small marine vehicles such as yachts, fishing trawlers and small research vessels. Trucks and buses generally operate at low loads at urban traffic. Aforementioned marine vessels also work at light loads particularly during inner-port operations and maneuvering conditions. Exhaust temperatures remain below 250°C at those cases since low loads generally require low fuel injection rate and high air-to-fuel ratio and thus, low in-cylinder temperatures. Although low temperature combustion is useful to keep NOx emission rates at low levels, it also degrades EAT unit effectiveness which mostly causes engine systems not to meet current emission regulations. Therefore, exhaust temperature management at low loads is critical not only for automotive vehicles but also small marine vessels.

Engine specifications are given on Table 1 below. The system operates at constant engine speed (1200 RPM) and constant engine load (brake mean effective pressure (BMEP) of 2.5 bar). As the engine system has six cylinders, a firing order of 1-5-3-6-2-4 is indicated on Table 1. Diesel fuel calorific value is assumed as 42700 kJ/kg in all those six cylinders.
**Table 1:** Diesel Engine Properties.

<table>
<thead>
<tr>
<th>Model</th>
<th>Four-stroke heavy-duty diesel engine</th>
</tr>
</thead>
<tbody>
<tr>
<td>Air intake</td>
<td>Turbocharged</td>
</tr>
<tr>
<td>Bore (mm)</td>
<td>107</td>
</tr>
<tr>
<td>Stroke (mm)</td>
<td>124</td>
</tr>
<tr>
<td>Compression ratio</td>
<td>17.3:0</td>
</tr>
<tr>
<td>Exhaust valve opening</td>
<td>20°CA BBDC</td>
</tr>
<tr>
<td>Exhaust valve closure</td>
<td>20°CA ATDC</td>
</tr>
<tr>
<td>Intake valve opening</td>
<td>20°CA BTDC</td>
</tr>
<tr>
<td>Intake valve closure</td>
<td>25°CA ABDC</td>
</tr>
<tr>
<td>Cylinder firing order</td>
<td>1-5-3-6-2-4</td>
</tr>
<tr>
<td>Calorific value of the fuel (kJ/kg)</td>
<td>42700</td>
</tr>
<tr>
<td>Operating speed and load</td>
<td>1200 RPM and 2.5 bar BMEP</td>
</tr>
</tbody>
</table>

Diesel engine model is demonstrated on Figure 1 below [Lotus engine simulation (2021)]. Fresh air flow is directed to the intake ports after getting compressed in the compressor and cooled in the intercooler. There are 2 intake valves per cylinder. Most modern diesel engines are equipped with double intake & exhaust valves. Thus, there are total 12 intake valves in the system. Intake valve is opened 20° Crank Angle (CA) degrees before top dead center (BTDC) and its lift rises as high as 8.5 mm. It is closed 25°CA degrees after bottom dead center (ABDC) as stated on Table 1. After the compression process, diesel fuel is directly injected into the cylinders and combustion creates the useful expansion work. Exhaust valves (similar to intake, total 12 valves) are opened close to the expansion process, 20°CA degrees
before bottom dead center (BBDC). Exhaust valve lift rises as high as 10.0 mm. Exhaust gas flows through the exhaust port and the turbine until valves are closed 20°CA degrees after top dead center (ATDC).

![Diesel engine model](image)

**Figure 1:** Diesel engine model

Two different sensors are placed on the diesel exhaust system on Figure 1. One of them is exhaust temperature sensor, responsible for determining the turbine-out exhaust temperature (°C) in the system. An EAT unit is not built in the model. Exhaust gas leaving the turbine is assumed to flow directly through the EAT system and maintain its effectiveness either at a low or high level, depending on the temperature of the flow. High exhaust temperature is desired through the EVPS strategy. The other sensor is exhaust flow rate sensor, responsible for measuring the exhaust mass flow rate (kg/min) streaming through the EAT system. High exhaust temperature is useful, however, EAT cannot be warmed up rapidly without a moderate flow rate. Therefore, effect of EVPS on exhaust flow rate is
considered as significant as exhaust temperature in the study. The model is used by the author on a former study to analyze the effect of exhaust valve opening (EVO) actuation on exhaust system heat up [Basaran (2020)]. It is seen that either advanced or retarded EVO can significantly improve exhaust gas energy. However, there is up to % 20 fuel consumption penalty which is a considerable disadvantage for practical application. Therefore, unlike aforementioned work, this study aims to examine a different approach – EVPS – which can improve exhaust temperature without causing an aggressive fuel inefficiency in the system.

1.2. Mathematical Formulations

Engine brake power, brake thermal efficiency, volumetric efficiency and combustion characteristics of the diesel engine are significant performance values to be considered. Brake power for the diesel engine – maintained constant in the analysis through fuel injection modulation – is calculated with [Heywood (2018)]:

$$P_b = \left[ \frac{V_d Z N (BMEP)}{60 n_r} \right]$$

In equation (1) above, Z is the total number of cylinders in the system, N denotes the engine speed (RPM) and $V_d$ shows the displaced volume. Another parameter in the formula – $n_r$ – denotes the number of revolutions the system needs to achieve in order to complete a cycle. As the model is a four-stroke diesel engine, $n_r$ is taken as 2. Finally, BMEP represents brake mean effective pressure which can be regarded as a measure how effective the in-cylinder pressure is kept
during both open and closed cycles of the engine system. In the analysis, other parameters in equation (1) does not change. However, BMEP can change due to the EVPS operation. In order to keep $P_b$ constant, fuel injection rate is actuated and BMEP is kept constant as 2.5 bar in the analysis.

Rising exhaust temperatures without considering the engine efficiency is not a complete analysis. The fuel efficiency is examined to assess the practicality of the method. It is found with [Heywood (2018)]:

$$\eta_{\text{brake thermal}} = \frac{3600 P_b}{m_{\text{fuel}} Q_{\text{LHV}}}$$  \hspace{1cm} (2)

In formula (2), $m_{\text{fuel}}$ denotes the flow rate (kg/h) of the diesel fuel directly injected into the cylinders. Moreover, $Q_{\text{LHV}}$ is the lower heating value of the diesel fuel which is assumed as 42700 kJ/kg.

Similar to thermal efficiency, volumetric efficiency has a considerable role in the study as it directly determines the flow rate of the exhaust gas. EAT warm-up does not only rely on exhaust temperature, but also exhaust mass flow rate. Therefore, the effect of the method on the volumetric efficiency needs to be considered. It is calculated with [Heywood (2018)]:

$$\eta_{\text{volumetric}} = \left[\frac{2 m_{\text{air}} 10^3}{30 N \rho_{\text{air}} V_d}\right]$$  \hspace{1cm} (3)
In equation (3), \( \rho_{\text{air}} \) represents the atmospheric air density charged into the cylinders and \( m_{\text{air}} \) is the fresh air flow rate.

Two-part Wiebe equations are utilized to simulate the combustion process inside the cylinders [Watson & Pilley (1980)]. This assumption considers the in-cylinder burning as two consecutive processes – premixed & diffusion parts – in the system. Every part assumes different formulations to calculate the burned mass fraction. The fractions for aforementioned particular combustion parts are found consecutively with:

\[
\begin{align*}
    m_{\text{premixed period}} &= 1 - 
    \left[ 1 - \left( \frac{\theta}{\theta_b} \right)^{C_1} \right]^{C_2} \\
    m_{\text{diffusion period}} &= 1 - e^{-A \left( \frac{\theta}{\theta_b} \right)^{M+1}}
\end{align*}
\]

In formulations (4) & (5) above, \( \theta_b \) is the total burn angle and \( \theta \) is the burn angle (in degrees). \( C_1 \) & \( C_2 \) in equation (4) and \( A \) & \( M \) in equation (5) are the coefficients in Wiebe combustion functions. \( C_1 \) & \( C_2 \) are taken as 2.5 and 2500, respectively. Also, \( A \) & \( M \) are assumed as 6.0 and 0.1, respectively.

1.3. Exhaust Valve Phase Shift Mechanism

Opening and closure timings of intake & exhaust valves at baseline are mentioned previously on Table 1. This numerical study focuses on the modulation of exhaust valve timings in the system. Intake valve timings (both opening and closure) are kept constant.
As shown on Figure 2 below, intake valve lift profile in all 6 cylinders remains constant. In other words, air-intake mechanism does not go through a change, engine breathing is not directly affected through the intake valves. However, both opening and closure timings of exhaust valves in all 6 cylinders are altered in the system. Both timings are advanced with 5°CA increments in the system until EVPS is adjusted 35°CA from the baseline position. The impact of this modulation on engine performance characteristics is intended to be observed.

![Exhaust valve phase shift mechanism](image)

**Figure 2:** Exhaust valve phase shift mechanism

2. **RESULTS AND DISCUSSION**

Utilizing the approach explained on the previous section, impact of EVPS on different engine performance parameters are presented on the following subsections.
2.1. Effect on Exhaust Temperature and Flow Rate

The effect of EVPS on turbine-out exhaust gas temperature and air-to-fuel ratio (AFR) is shown on Figure 3 below. Exhaust valve phase is altered with 5°CA increments in the system until it gets 35°CA from the baseline. It is observed that at slight shifts, there is not a significant change on exhaust temperature. However, at moderate and aggressive shifts (particularly above 15°CA), exhaust temperature rises rapidly in the system. This is partially due to the reduction on AFR indicated on Figure 3. AFR behaves directly downward especially after a shift of 15°CA from the baseline. The decreasing trend of AFR seems to be inversely proportional with the increase on exhaust temperature.

![Figure 3: Effect of EVPS on exhaust temperature and air-to-fuel ratio](image)

The reason behind the sudden fall on AFR can be derived from Figure 4 below. Engine volumetric efficiency goes through a sudden change after 15°CA during the phase shift. A noticeable decrease on
volumetric efficiency is obtained at extreme shift of exhaust valves (35°CA from the baseline) which enables up to 75°C exhaust temperature rise on Figure 3. The increase on temperature is more than adequate to keep the diesel exhaust unit above 250°C.

![Graph showing volumetric efficiency and exhaust flow rate](image)

**Figure 4:** Effect of EVPS on volumetric efficiency and exhaust mass flow rate

The negative effect of the method is also seen on Figure 4. As the volumetric efficiency decreases, lower in-cylinder fresh air charge is maintained during steady-state operation and thus, lower exhaust gas flows through the EAT system. Although there is a dramatic exhaust flow reduction in the system, it is still seen on Figure 3 that the engine system can reach effective EAT temperatures through increased exhaust temperatures (exceeding 250°C). This is certainly not possible with nominal-valve-timing operation where exhaust temperature remains below 200°C.

Another direct effect on exhaust temperature is demonstrated on Figure 5. In-cylinder residual exhaust gas steadily increases as EVPS is modified. Higher residual gas is mixed with the fresh ambient air
and provides a hotter environment inside the cylinders. Therefore, as percentage goes up due to early exhaust closure, exhaust temperature boosts rapidly. In contrast to AFR and volumetric efficiency on Figure 3 & Figure 4, it can be derived that residual gas percentage is directly proportional with the exhaust temperature on Figure 5. However, as the system acquires more residual gas with the control of EVPS, lower exhaust gas is allowed to flow through the EAT and thus, a considerable exhaust mass flow rate reduction is observed on Figure 4. That reduction can be considered as the cost of rising exhaust temperature above 270°C. Another significant result is that the system does not need the highest shift (35°CA) to keep exhaust temperature above 250°C. A relatively lower shift (30°CA) can maintain the effective temperature with higher exhaust flow rate on Figure 4.

**Figure 5:** Effect of EVPS on exhaust temperature and residual gas percentage
2.2. **Effect on Engine Fuel Consumption**

Rising exhaust temperature causes fuel consumption penalty as seen on Figure 6 below. As mentioned in the Introduction section, all conventional strategies including delayed fuel injection, EEVO, electrical heating and afterburner usage result in either high fuel or high energy consumption in order to improve exhaust temperature in diesel engine systems. However, those aforementioned methods generally require more than % 10 rise on fuel consumption and EVPS seems to acquire similar exhaust temperature improvement with only % 7.5 rise on BSFC. Therefore, this can be regarded as the advantage of the method compared to traditional techniques which are fuel-inefficient and already in active use in heavy-duty diesel vehicles.

![Figure 6: Effect of EVPS on pumping loss and brake specific fuel consumption](image)

The reason the system needs more fuel consumption with EVPS is that engine pumping loss rises in the system. Early exhaust closure causes the recompression of the remained exhaust gases inside the
cylinders and thus, engine system is faced with higher pumping loss during moderate and extreme applications of EVPS. As Figure 6 is examined, it can be derived that whenever pumping loss rises, more fuel is injected into the cylinders in order to keep engine load constant at 2.5 bar BMEP. As the power is required to be maintained similar to the nominal condition, BSFC starts to increase to compensate the extra pumping loss. Rise of fuel consumption affects brake thermal efficiency (BTE) negatively as shown on Figure 7 below. BTE reduces from % 32 to almost % 29 due to high pumping loss. IMEP\textsubscript{power} – power producing potential of the engine – climbs dramatically through increased fuel injection on Figure 7. At nominal condition, an IMEP\textsubscript{power} close to 3.6 bar is adequate to keep engine load constant at 2.5 bar BMEP. However, at moderate and extreme implementations of EVPS, IMEP\textsubscript{power} increases rapidly almost up to 4.0 bar in order to overcome the additional pumping loss. It is explicitly seen on Figure 7 that the system recovers its inefficient performance by increasing IMEP\textsubscript{power}. 
2.3. Effect on Exhaust After-treatment Warm-up

Now, finally the impact of EVPS on EAT heat-up is compared with a conventional thermal management technique – EEVO – on Figure 8 below. Results of EEVO mode are taken from a previous work [Basaran (2020)]. Calculation of heat transfer rates from the exhaust gas flowing out of the diesel exhaust unit to the catalyst inside the EAT system depends on the formulation below [Incropera (2007)]:

\[
\dot{Q} = C[\dot{m}_{\text{exh}}]^{4/5} [T_{\text{exhaust}} - T_{\text{EAT catalyst bed}}] 
\]

In equation (6), \( \dot{m}_{\text{exh}} \) is the exhaust flow rate (kg/min), \( C \) is an EAT-dependent constant, \( T_{\text{exhaust}} \) and \( T_{\text{EAT catalyst bed}} \) denote the turbine-out exhaust temperature (°C) and EAT bed temperature (°C), respectively. Heat transfer rates are normalized considering the heat transfer rate obtained at 0°C EAT temperature for nominal engine mode is 1.0.
As Figure 8 is analyzed, both EVPS and EEVO techniques are better than nominal engine mode at improving EAT system temperature. Nominal mode can warm up the after-treatment system only close to 200°C which is insufficient for effective emission reduction. EEVO is found to be the most effective methods at cold temperatures (below 50°C) due to its relatively higher exhaust temperature (225°C) and exhaust flow rate compared to nominal mode [Basaran (2020)]. Although it rises fuel consumption penalty at a rate of % 9.6, it improves heat transfer rates up to % 22 which is highly beneficial at cold EAT temperatures. Unlike EEVO, EVPS leads to lower fuel consumption penalty (% 6), but it cannot enhance EAT warm-up that much during cold temperatures due to the dramatic exhaust flow rate reduction shown previously on Figure 4. However, it can rise exhaust
temperature above 250°C which neither EEVO nor nominal mode can achieve on Figure 8. Thus, it improves EAT heat-up more than both nominal and EEVO mode – up to % 90 – when temperature is maintained above 50°C. Also, as the heat transfer rates below the “zero heat transfer line” are examined, EVPS has lower negative heat transfer rates compared to both EEVO & nominal modes due to low exhaust flow rates. This can be advantageous for EVPS technique for delaying the EAT Cool-off more than other methods.

**CONCLUSION**

In this study, EAT improvement on a heavy-duty diesel engine system is investigated through using a one-dimensional engine model. EVPS technique is examined on the model at a low-loaded condition for increased exhaust temperature and thus, improved EAT effectiveness. The results demonstrate that 35°CA shift of exhaust valve phase is sufficient to rise exhaust temperature up to 75°C which can keep the exhaust unit temperature and thus, EAT temperature above 250°C. It is seen that increase of exhaust temperature is inversely proportional with the AFR and the volumetric efficiency and directly proportional with the residual exhaust gas percentage in the system. EVPS seems to boost the exhaust temperature via both air flow reduction and rise of BSFC. High pumping loss accounts for the moderate fuel consumption penalty (up to % 7.5) which is relatively low compared to the penalty (more than % 10) achieved with conventional methods. EVPS cannot improve the EAT warm-up as much as EEVO at low EAT bed temperatures (below 50°C) due to low exhaust flow rate.
However, it is superior to EEVO at higher EAT bed temperatures (above 50°C) – rising heat transfer rates up to % 90 – as it can improve exhaust temperature more. EVPS is also effective at enhancing negative heat transfer rates. Since EVPS is fuel-saving compared to traditional strategies, it can be a practical method for EAT heat-up in automotive & marine vehicles.

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