Burglary and Control Systems: An Interdisciplinary Approach at the Intersection of Engineering and Criminology

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Highlights

- Innovative application of control systems theory to model burglary processes.
- Integration of machine learning for analyzing burglar behavior patterns.
- Novel perspective combining engineering principles and criminology.

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- Abstract

The subject investigated in this study is the modeling of control systems into real life. This research is focused on the issue of burglary. While modeling the internal process as a system, how a thief who enters a house makes decisions about what he does inside the house, the question of how age, experience, plan and environmental factors affect the outcome of the burglary has been mathematically examined. Machine learning algorithms and supervised learning models were used when designing the control system and giving meaning to the data. In this research, the MATLAB program helps the analysis by providing information about how much the thief's performance can improve, that is, the potential of his performance, as a helper in the controller design. The research shows that engineering can be applied to real-life events. It creates a new perspective for early detection of the aspects in which security measures should be improved, possible scenarios, and for expanding the area of control systems.

- Keywords

Burglary, Control Systems, Machine Learning, Performance Optimization, System Design.

- Introduction

Burglary is a crime that humans began encountering as they transitioned into societal living. With the progression of humanity and the increase in property ownership, burglary diversified and became more prevalent, standing out as one of the most prominent crimes today [1]. For years, people have felt the need to take precautions against criminal elements that threaten them. As technology and electronics have inevitably affected and developed our lives in recent years, electronic security systems have also become a part of our lives [2]. Many control systems have been designed and implemented for the crime of burglary, which directly threatens our life and property security [3]. We aim to design our control system based on the behavior of the real burglar by considering these control systems from a different perspective.

A control system is defined as a set of physical elements combined to command, direct, or regulate itself or another system [4]. Control systems manage, control or regulate the behavior of devices or systems using a control loop [5]. In other words, control systems aim to control the outputs of the processes at a desired constant value, to ensure that the outputs of the processes follow a certain change form, and to ensure that events occur within a certain secret [6]. For example, we may want the speed of a car on the highway to remains as close as possible to 60 miles per hour in spite of possible hills or dverse wind; or we may want an aircraft to fallow a desired altitude, heading, and velocity profile independent of wind gusts. These are realized thanks to control systems [7].

We can talk about the control system in controlling values such as speed, temperature, humidity, voltage and we can derive their equations in line with numerical values. “So can we say this systematization for the actions we take in our lives?” By asking the question, we aim to define burglary, which poses a great risk in our lives, as a control system. The process that begins with the burglar entering the house actually includes a complex decision-making and implementation chain where many factors are evaluated together. Before entering a house, the burglar examines the environment, evaluates the risks, calculates the time he will spend inside and determines the most appropriate action plan for himself. This process unknowingly turns into a control loop, where many parameters such as environmental factors, the experience of the burglar, the difficulties he may encounter and the targeted profit come together and shape the behavior of the burglar. Within the scope of this article, we will try to answer the questions of whether we can express this complex process with a numerical model or analyze the actions of this burglar within the framework of a control system.

In answering these questions, we will get support from machine learning, a sub-layer of artificial intelligence. They are trained to make classifications and predictions using statistical methods. With existing big data, it forms the basis for producing predictable results in the future [8]. Because of these features, we will use machine learning while processing the statistics we collect from different articles and data.

The data we use in this article has been prepared in accordance with certain sources and statistics. However, since the data presented in the sources does not always include all the details, the missing parts have been completed with logical inferences. For example, a source may have provided general information and rates about certain age groups and experience levels, but the exact relationship between these two variables has not been given. In such cases, the missing data was created as an estimate and used in modeling the system. These estimates were collected from 20 different sources in a logical direction and in a way that supports general percentages. While making estimates, they were created in accordance with the data mentioned in the articles.

In this study, the process from the burglar’s entry to the house to his exit will be handled as a control system with an unconventional approach. Variables affecting the burglar’s behavior - his age, experience, planning ability, environmental factors and negative situations he may encounter - will be quantified and analyzed. For example, an engineering model of the process will be created based on parameters such as entry time into the house, time spent inside and the value of the stolen goods.

The performance of the burglar will be evaluated in the control models created. As a result, performance improvement will be made. Compensators are added to change the closed loop performance in control systems [7]. Since we want to control the data such as reducing errors or speeding up the process, we aimed to use lag compensator and lead compensator.

We will carry out this process with MATLAB, which integrates calculation, visualization and programming environment [9]. This application will be a great advantage for us due to its ability to handle complex data structures, built-in editing and debugging tools, and ease of use in mathematical and engineering calculations [10].

This article aims not only to present a theoretical control system analysis, but also to provide a new perspective on the usage areas of control systems with an unusual example from daily life. burglary is a phenomenon that is often studied in security solutions such as alarm systems, sensors and cameras. However, in this study, a different approach was adopted and the burglary process was evaluated from an automation system perspective. This perspective reveals the wide-ranging applicability of control systems and how they can be used in process optimization, rather than just designing a security mechanism.

As a result, this study aims to both add a new dimension to the concept of control systems and show unusual ways of interpreting daily life events with the engineering principle. In this context, we aim to offer a creative perspective to engineering designs by addressing a phenomenon such as burglary with a systematic approach.

- **Logical Reasoning and Drawing Conclusions**

Logical reasoning and deduction are one of the basic functions of the human mind. Logic is a tool that helps us understand the world around us and reach correct conclusions. Logical reasoning is the process of reaching logical conclusions from a given proposition or situation. Logic is a way of thinking based on a set of principles, and we use these principles to reach correct conclusions. Logical reasoning gives us the ability to evaluate arguments and reach logical conclusions. Clear concepts, accurate definitions, and arguments are very important in the logical reasoning process [11]. The article uses the logical reasoning method. The reason for this is that the information in the sources where the research was conducted and data was collected does not specify all the details in detail. For example, the data from a study conducted in Korea are as in Table 1 and Table 2. [12]. In this table, we can access data such as age ranges, the number of people in these age ranges, and the number of burglaries they commit. However, the age of a certain person and the number of burglaries they commit are not clearly mentioned.

NUMBER OF LIFETIME BURGLARIES	NUMBER	PERCENTAGE
Fewer than 10	18	34.6
Between 10 and 49	19	36.5
Between 50 and 99	10	19.2
More than 99	5	9.6

Table 1: Number of Lifetime Burglaries To Date, per subject

AGE	NUMBER	PERCENTAGE
13-20	27	51.9
21-30	10	19.2
31-40	8	15.4
41-50	5	9.6
51 and over	2	3.8

Table 2: Age Distribution of the Sample

Similarly, FOX 5 Atlanta news channel interviewed 99 thieves in 2018 and asked them 20 different questions [13]. The interview data was also shared as percentages, as shown in Visual 1 and Visual 2.

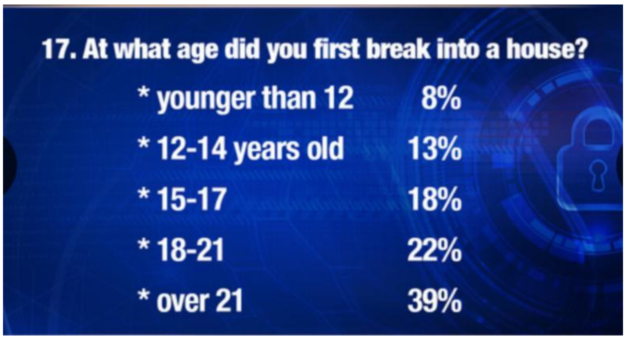

Figure 1: Interview Question 17

Figure 2: Interview Question 18

Data from 20 different articles and statistics, such as these articles and interviews, have been evaluated, combined, and logical inferences have been made [12-16, 24-38]. In these articles, not only the numerical ratios of individuals but also how they made their target choices, how long it took them to complete their actions, and the parameters they paid attention to during the burglary process were analyzed and logical inferences were made. For example, in an article prepared in the UK, it was stated that in unplanned burglaries, the damage amounted to 800 pounds, while in planned ones, the damage ranged from 1,000 to 10,000 pounds. Additionally, it was expressed that 90% of the thieves studied followed a consistent and systematic pattern in their search strategies [14]. Another study reported that experienced thieves started stealing at the age of 11. Inexperienced thieves started stealing at the age of 17 [15]. It has been reported that inexperienced people stay in each room for about 20 seconds [16]. In this way, the literature has been reviewed, and the information collected to make logical inferences has been grounded on a solid basis. As a result, an Excel table has been created for 100 different data points that can be used for machine learning. Since these formations are not from a single source and do not provide exact results, the estimated data created have been used to understand the system's modeling. The aim of this approach is to demonstrate how the system will be designed based on real data, assign a controller, and analyze the functionality of this controller. The data used have been regarded as a tool to explain the operation of the control system and the design process. As a result, the methods and analyses discussed in this paper will be modeled in accordance with the data used and in alignment with the theoretical framework of the study.

- **Machine Learning and Data Analysis**

Machine Learning is an application of Artificial Intelligence (AI) thatprovides systems the ability to automatically learn and improve from experience without beingexplicitly programmed [17]. Machine learning is examined under 3 main headings.

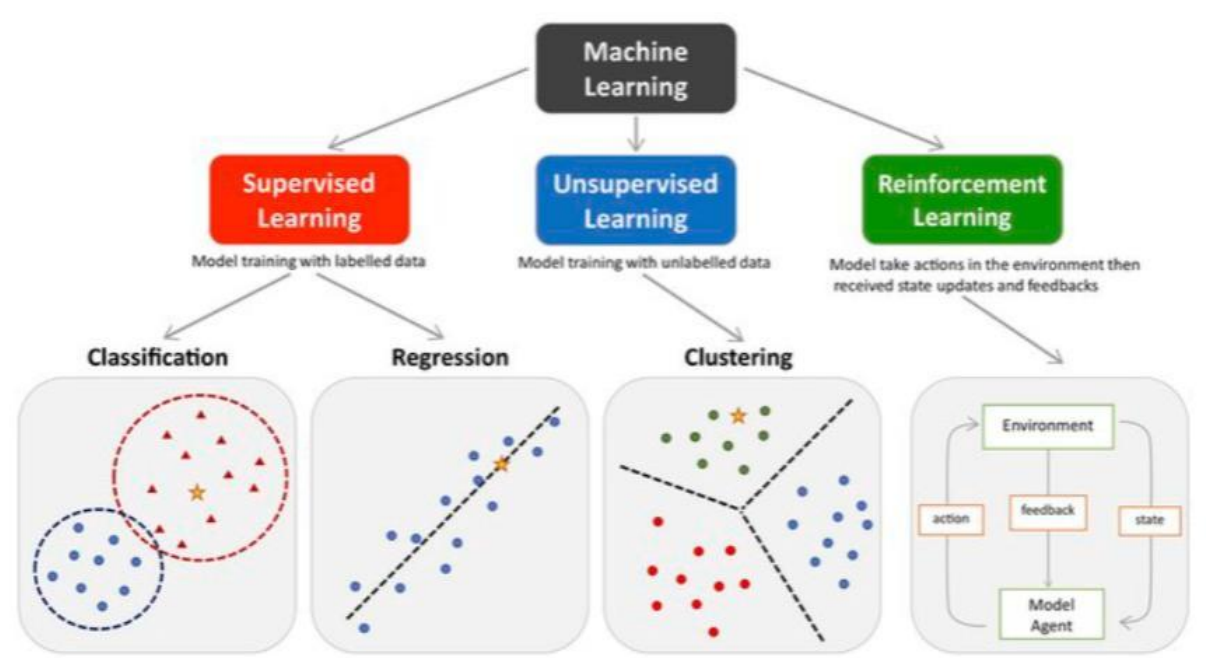

Figure 3: Types of Machine Learning [18]

The goal of supervised learning is to build an artificial system that can learn the mapping between the input and the output, and can predict the output of the system given new inputs [19]. Supervised learning classified into two categories of algorithms.

i. Classification: A classification problem is when the output variable is a category, such as“Red” or “Blue” or “Disease” or “No disease”

ii. Regression: A regression problem is when the output variable is a real value, such as“Dollars” or “Weight” [17].

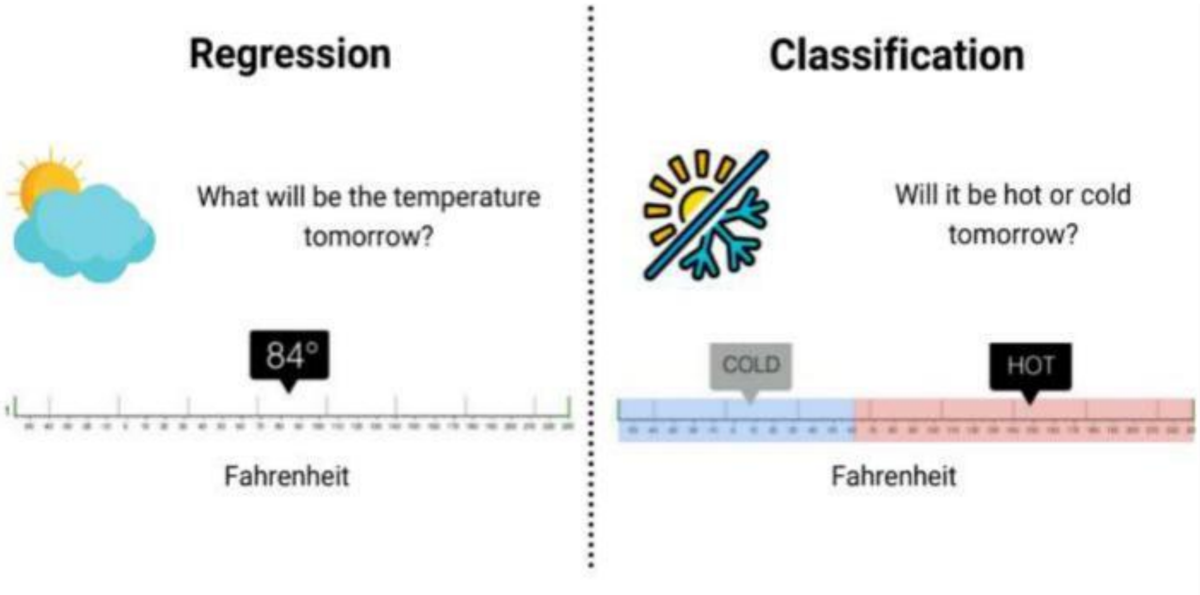

Figure 4: Difference Between Regression and Classification [17]

Unsupervised learning refers to the use of artificial intelligence (AI) algorithms to identify patterns in data sets that contain unclassified or unlabeled data points [20].

Finally, rainforcemend learning It is a learning method where a software agent interacts with an unknown environment, selects actions, and progressively discovers the environment dynamics [21].

In our study, we examined the subfields of machine learning and determined that the supervised learning approach was the most suitable for our work. As part of this approach, we utilized classification to distinguish between urban and rural areas, coding urban areas as 1 and rural areas as 0. Following the classification, we used the regression method for further analysis.

- As shown in Figure 5, the variables used in our analysis and their impacts are defined as follows:
- Age of the burglar, burglar experience, house location (urban/rural), and planning time are identified as the main factors influencing the time spent at the house.
- Time spent at the house affects the amount of goods stolen.

Additionally, ownership status (rent or ownership) and household income are other variables that influence the amount of goods stolen.

These variables and their relationships are visualized in Figure 5, which clearly demonstrates the causal links and supports our analysis.

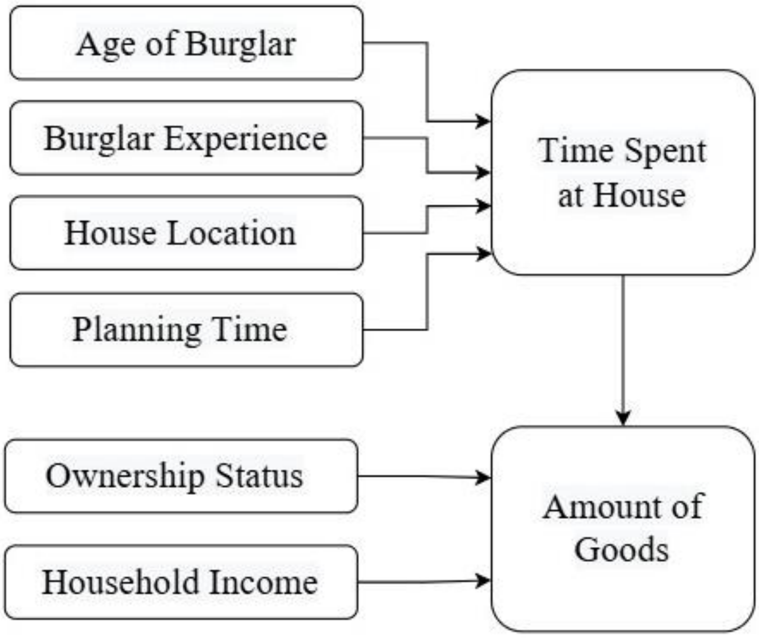

Figure 5: Burglary Analysis Flowchart

We determined the time spent at home (Ts) for each burglar using four different parameters. However, for some burglars, certain data related to these parameters was inaccessible. To fill in the missing data, we used the weighted scoring method to predict the missing parameters. In the weighted scoring method, a specific weight is assigned to each parameter, and predictions are made for the missing data based on these weights. This allowed us to complete our data by filling in the missing values with selected predictions. We found these values as shown in the equations [22].

$$Ts = \alpha_0 + \sum(\alpha_i \cdot X_i)$$

Equation 1: Ts

$$Ts = \alpha_0 + \boldsymbol{\alpha}^T \cdot \mathbf{X}$$

Equation 2: Ts

$$Ts = \alpha_0 + \begin{bmatrix} \alpha_1 & \alpha_2 & \alpha_3 & \alpha_4 \end{bmatrix} \cdot \begin{bmatrix} \text{age} \\ \text{experience} \\ \text{urban/rural} \\ \text{planning} \end{bmatrix}$$

Equation 3: Ts

Here, the constant term is determined as 3. This value represents the time spent at home when all parameters are zero. That is, when the effect of all other parameters is ignored, the time the burglar spends in the house is 3 units. This value represents the initial (reference) value of the model, and the effects of all other parameters are added to this value. For example, regardless of the values of parameters such as age and experience, the time spent at home is considered to be 3 units at the starting point of the model. It is used in our formula as follows:

$$Ts = 3 + \alpha_1 \cdot X_1 + \alpha_2 \cdot X_2 + \alpha_3 \cdot X_3 + \alpha_4 \cdot X_4$$

Equation 4: Ts

We performed these operations using the Regression Learner section of the MATLAB application. We processed our Excel table to Regression Learner. As a result of the table we processed, we taught the machine these situations. We analyzed how many errors there were in the estimated values and how accurate the estimates were by examining this table. Based on the features provided to the machine learning model, we tried to estimate how long it would take for the burglar to leave the house or the value of the items he would steal. As shown in the figure 6,7,8,9,10,11,12 below, we observed the effect of the mentioned inputs on time spend. We understood that the age of the burglar was the most effective in terms of time spend output.

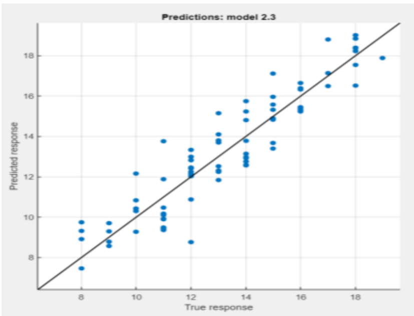

Figure 6: Predicted vs Actual (Validation)

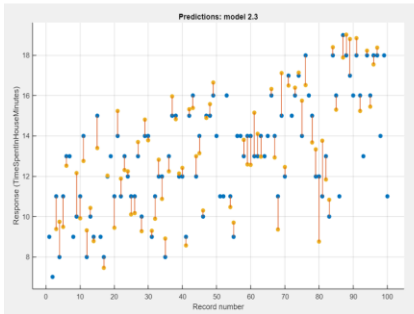

Figure 7: Time Spent in House vs Record Number

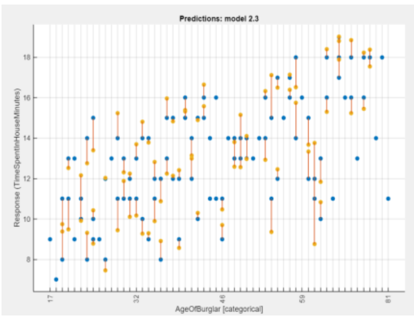

Figure 8: Time Spent in House vs Age of Burglar

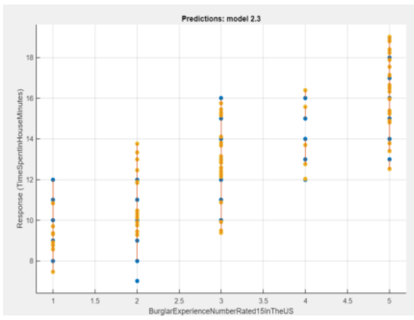

Figure 9: Time Spent in House vs Burglar Experience

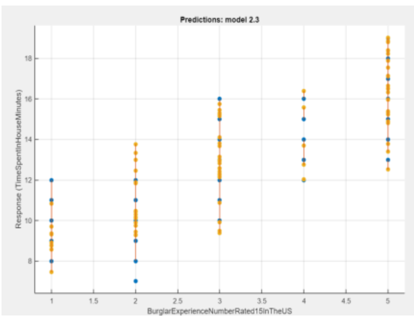

Figure 10: Time Spent in House vs Burglar Experience

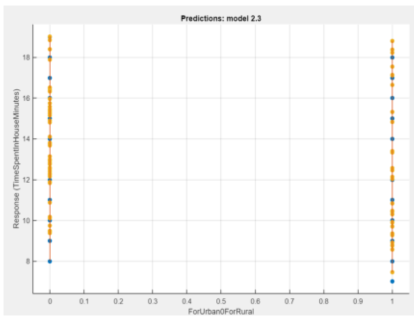

Figure 11: Time Spent in House vs Urban/Rural

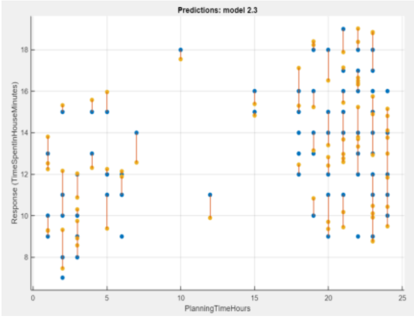

Figure 12: Time Spent in House vs Planning Time

Based on the relationships mentioned earlier and whose diagram we see in Figure 5, we created the graphs created for the time spent at home in the same way for the amount of money stolen. In Figures 15,16,17,18,19,20,21 we examined the connection of each input with the amount of money stolen. As a result, we observed that the time spent at home and the experience of the burglar affected the amount of money stolen the most.

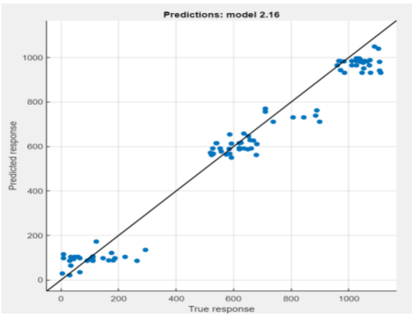

Figure13: Predicted vs Actual (Validation)

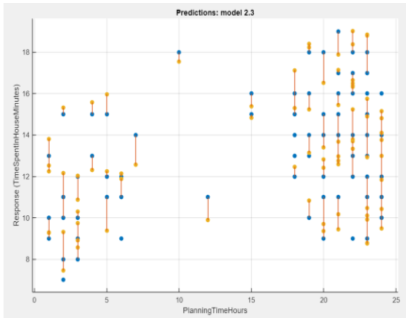

Figure14: Amount of Goods vs Record Number

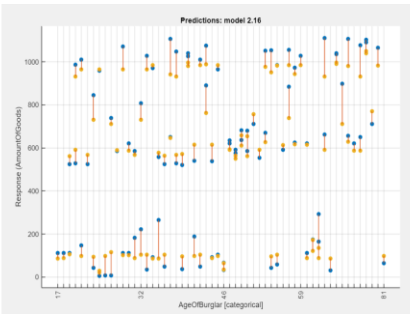

Figure 15: Amount of Goods vs Age of Burglar

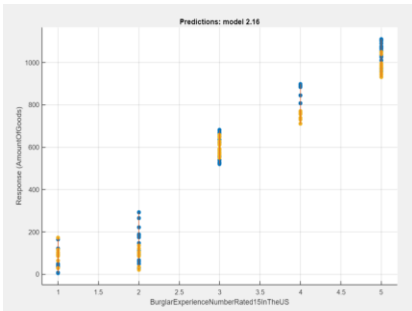

Figure 16: Amount of Goods vs Burglar Experience

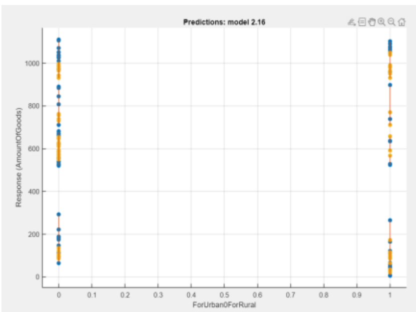

Figure 17: Amount of Goods vs Urban/Rural

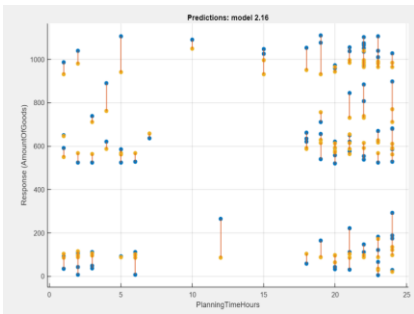

Figure 18: Amount of Goods vs Planning Time

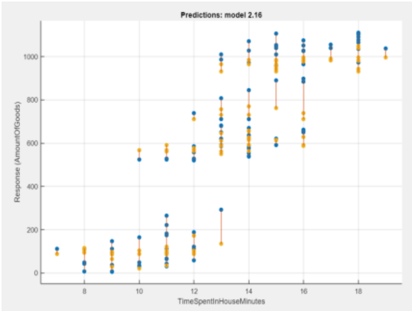

Figure 19: Amount of Goods vs Time Spent in House

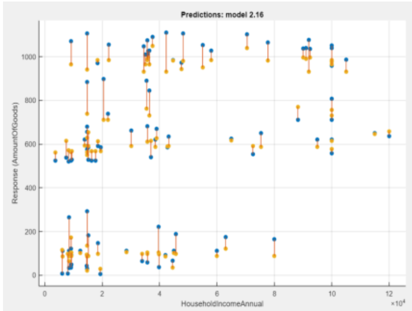

Figure 20: Amount of Goods vs House Hold Income

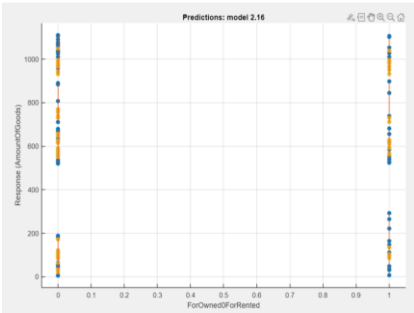

Figure 21: Amount of Goods vs Ownership Situation

As a result of these actions, the machine will now recognize our inputs and estimate the time spent and amount of goods data accordingly. After this process, we will examine how we can digitize a burglar's process by referencing these tables, how we can systematize it, and how we can make improvements under the controller title.

- **Burglars to System Design**

In the control system I aim to design for burglary, we will digitize and assign the available data. First, we defined the schematic of our system as shown in Figure 22. As seen in the figure, our system is a closed-loop system. The actuator in this system is defined as the burglar, the input is entry into the house, and the output is the amount stolen by the burglar as a result of the burglary. The controller will be defined as a lag/lead compensator, which will be discussed in the next section. The reason for this definition is to address the question of how we can improve the burglar's performance.

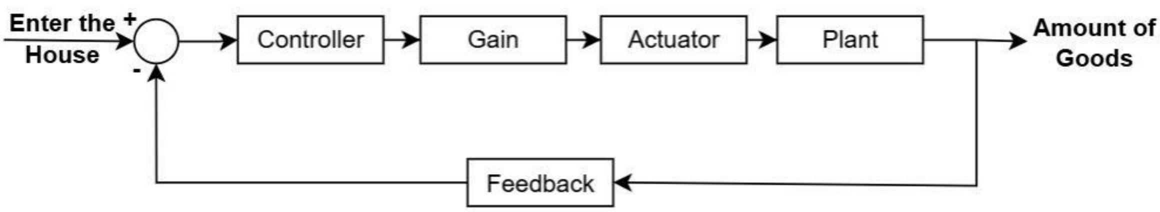

Figure 22: Burglary System

The plant is represented by the diagram in Figure 23. The plant is defined as the inputs discussed in the previous section and the time spent inside the house that is influenced by these inputs.

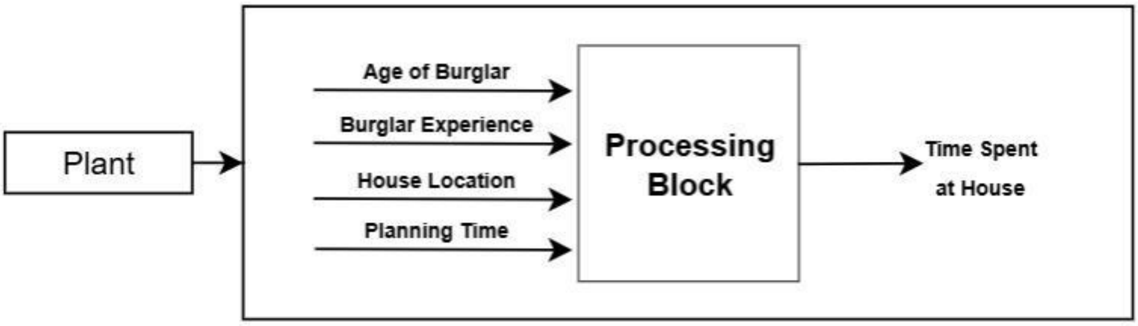

Figure 23: Plant Design

After determining our control system, we found that the most suitable definition for digitizing our system is the second-order system design. The transfer function of the second-order system is specified in Equation 5 [23].

$$y(s) = \frac{K{\omega_0}^2}{s^2 + 2\zeta\omega_0 s + {\omega_0}^2} u(s) \equiv \frac{K}{(\frac{s}{\omega_0})^2 + 2\zeta\frac{s}{\omega_0} + 1} u(s)$$

Equation 5

We defined the time from the beginning to the end of the burglary as the settle time (Ts). The formula for settle time is shown in Equation 6. From this formula, we derived the product of the damping ratio (ζ) and the natural frequency (ωn) values.

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

Equation 6

Since the damping ratio of the burglars we selected is inversely proportional to their experience, we defined the most experienced burglar's damping ratio as 0.1. The least experienced burglar's damping ratio was defined as 1. Following this definition, we used the formula shown in Equation 6 to calculate the natural frequency (ωn).

Then, we calculated the value of K in Equation 5. We performed this calculation as shown in Equation 7.

$$\mathbf{K} = K_{\text{ownershipstatus}} \times K_{\text{householdincome}}$$

Equation 7

The constant K mentioned here is a fixed number and is expressed as gain. The gains for the ownership status and the house holding come values were determined based on information we previously gathered from articles. If the house being burglarized belongs to the homeowner, the gain increases by a factor of 1.2. Similarly, if the annual income of the house is high, the burglar's gain increases accordingly. The formulas for these values are shown in Equation 8 and Equation 9..

$$K_{\text{ownership}} = 1 + 0.2 \cdot \theta$$

Equation 8

$$K_{\text{householdincome}} = \frac{I}{I_{\text{normal}}}$$

Equation 9

The value of θ shown in Equation 8 is defined as 1 if the house being burglarized is not a rental, and 0 if it is a rental. The value of Inormal specified in Equation 9 is set to 41,000$, which is the average of the data we have. Based on these numerical assignments, we constructed our system.

The data of the three burglars we selected is shown in Table 3.

	Age	Experience	Urban(1)/ Rural(0)	Planning (hours)	Times(Ts) (minutes)	Household Income ($)	Ownership Status (1)/ Rented (0)	Amount of Goods ($)
1	18	2	1	2	7	8.500	1	111
2	38	5	1	15	15	34.500	0	1047
3	61	2	0	24	11	63.000	0	175

Table 3: Burglar Data

In this table, experience is defined on a scale from 1 to 5, with 5 assigned to the most experienced and 1 assigned to the least experienced. Based on this data, the damping ratio, natural frequency, and gain calculations for the burglars are shown in Table 4.

	Damping Ratio (ζ)	Natural Frequency (ωn)	Gain (K)
1	0.8	0.71	0.25
2	0.2	1.3	0.84
3	0.7	0.52	1.53

Table 4: Transfer Function Parameters

Based on these parameters, the transfer function has been calculated as shown in Equation 5. These calculations and the burglars' graphs were created using MATLAB. The graphs for each burglar are shown in Figure 24, Figure 25, and Figure 26. In these graphs, the step responses represent the burglar's performance. This performance is defined as the ratio of the stolen money to the time spent inside. The maximum performance of each burglar is defined as 1 on the graph. Here, each burglar's goal is to maintain the best performance consistently throughout the time spent inside.

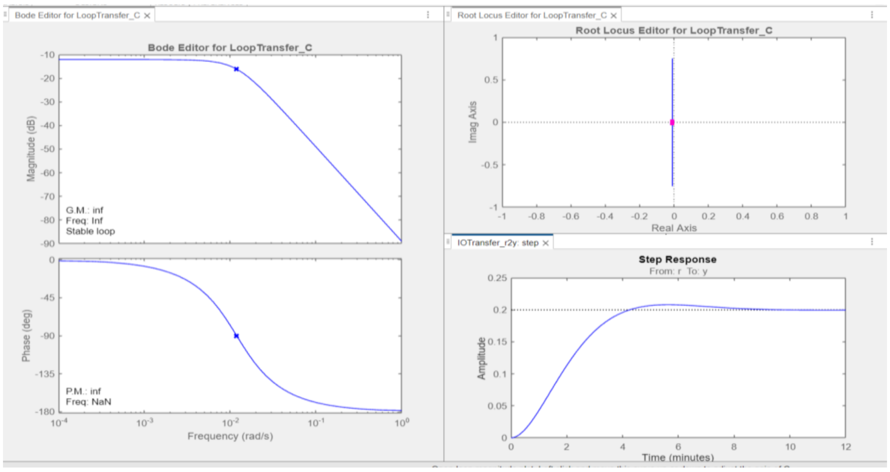

Figure 24: Burglar 1 MATLAB Graphics

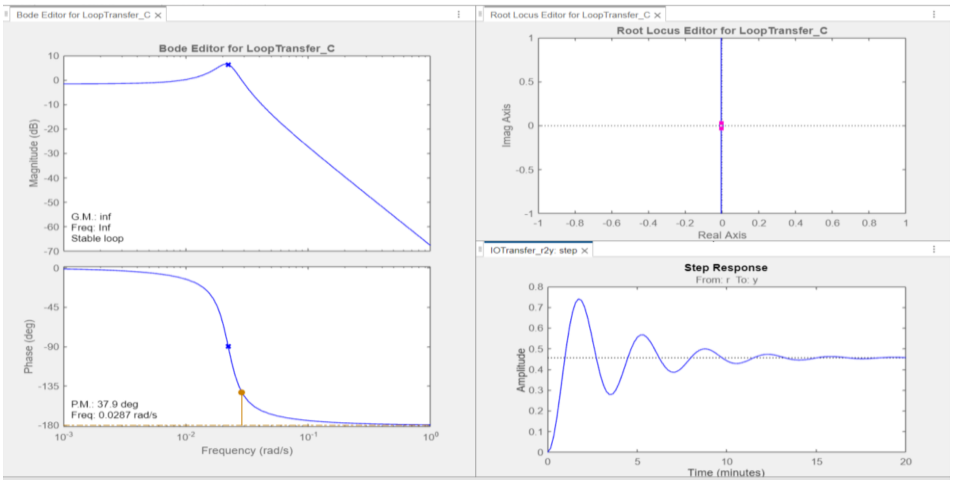

Figure 25: Burglar 2 MATLAB Graphics

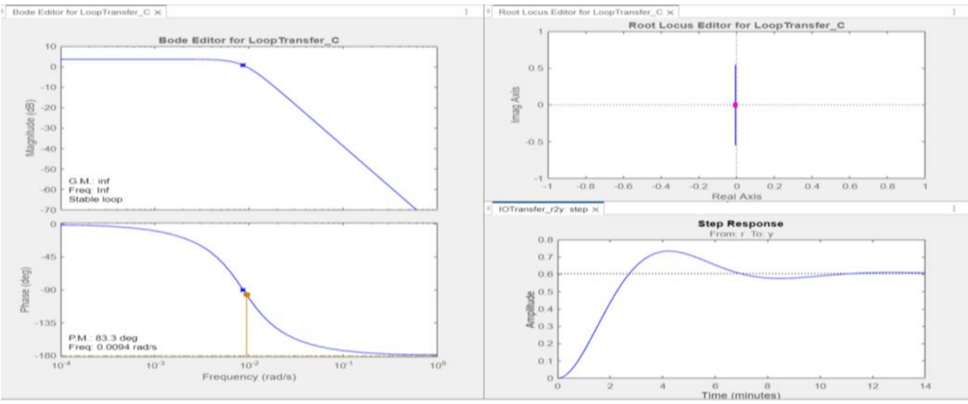

Figure 26: Burglar 3 MATLAB Graphics

In light of these graphs, we commented on the characteristics of our burglar and determined whether they need a controller and, if so, which type of controller they require.

- **Controller Design**

First, we examined our burglars and made comments about them. As mentioned, each burglar wants to maintain their best performance consistently. For this reason, based on the analyzed graphs, we determined the controller each burglar needs and designed it. We identified that the first burglar is young and inexperienced. While a young burglar can move quickly, the likelihood of making mistakes is very high due to inexperience. Therefore, we first designed a lag compensator for this burglar. The equation and graphs of the compensator are shown in Figure 27 of the MATLAB application.

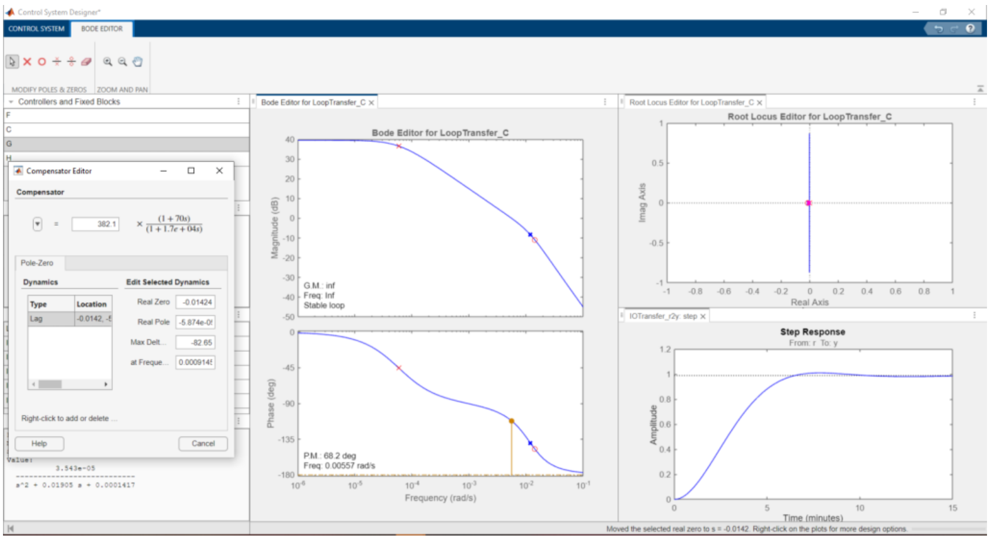

Figure 27: Burglar 1 After Lag Compansator

After reducing the error, we designed a lead to shorten the time the first burglar spends in the house. Its graphs and equation are shown as in Figure 28.

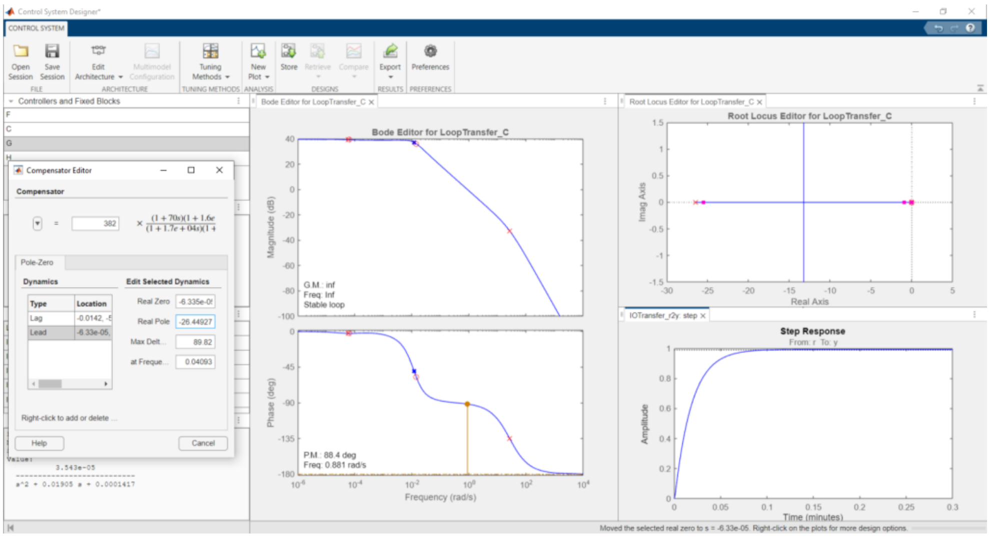

Figure 28: Burglar 1 After Lead and Lag Compansator

When we examined our second burglar, we observed that the burglar is experienced but advanced in age. In light of this information, we first wanted to shorten the time spent in the house and added a lag compensator. The formula and graphs of the added lag compensator are shown in Figure 29.

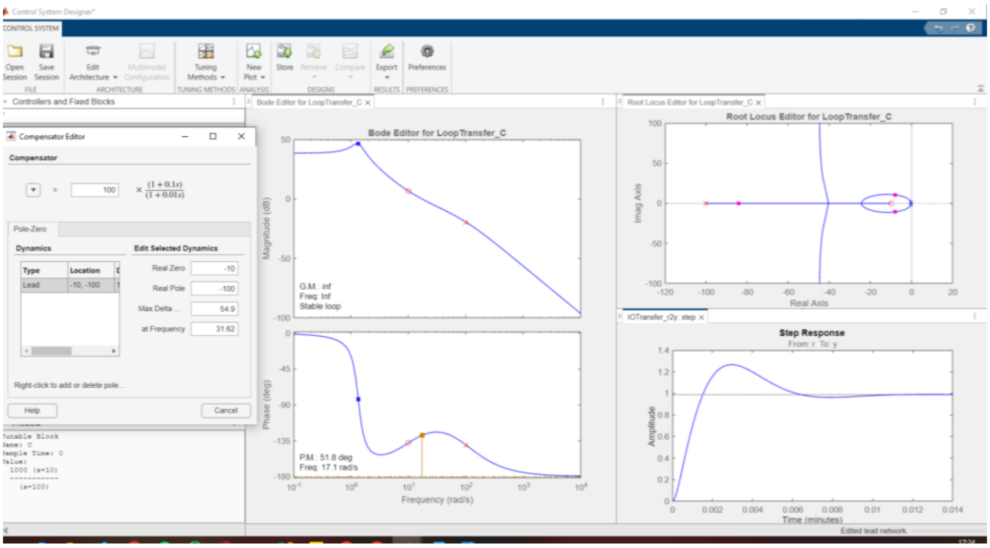

Figure 29: Burglar 2 After Lead Compansator

Then, since we wanted to reduce the error coefficient of the second burglar as well, we added a lag compensator. The data with the lag compensator is shown in Figure 30.

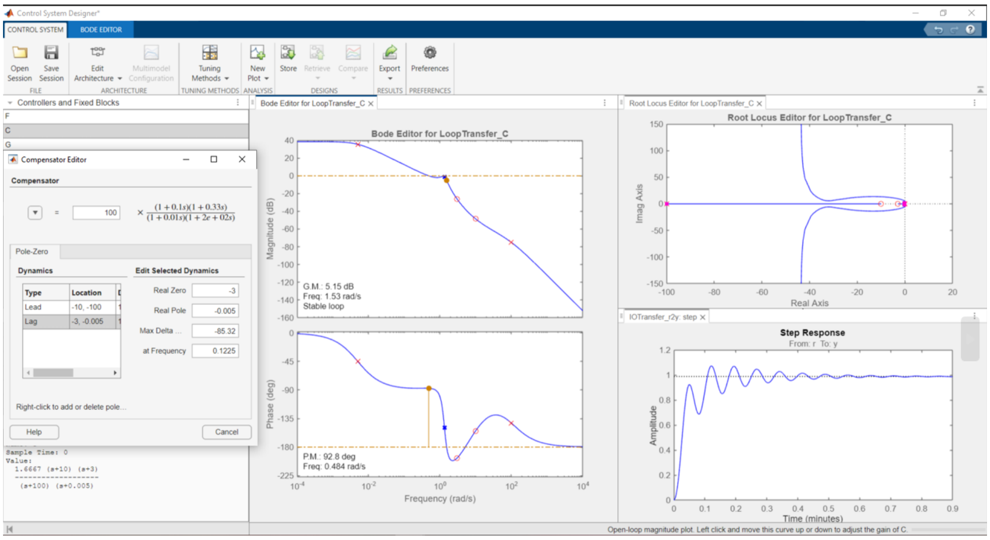

Figure 30: Burglar 2 After Lead and Lag Compansator

Finally, by examining our third burglar, we determined the controller they needed. This burglar is elderly and less experienced. For this burglar, we first designed a lead. The result of our designs is as shown in Figure 31.

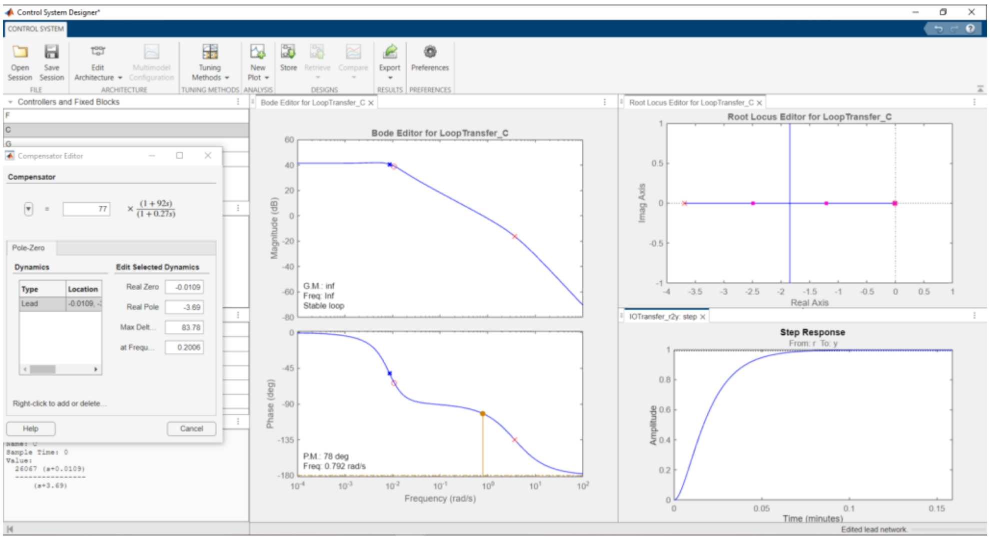

Figure 31: Burglar 3 After Lead Compansator

As a result of this design, we concluded that the third burglar does not need a lag compensator. And at the end of the day, we checked by quantifying an event from daily life.

- **Discussion**

This study has introduced a novel approach to understanding burglary by treating it as a process governed by control systems. By quantifying variables such as burglar experience, planning, and environmental factors, we could analyze their impact on time spent at the crime scene and the value of stolen goods. Machine learning models provided critical insights into the relationships between these variables, highlighting age and experience as primary influencers.

The use of compensators for performance improvement illustrates the practical application of control theory in unconventional settings. The lag and lead compensators effectively addressed different aspects of burglar performance, such as reducing errors or optimizing time spent. These findings align with the broader goal of control systems—to regulate and improve processes—showcasing their adaptability beyond traditional engineering domains.

- **Conclusion**

The study demonstrates the potential of applying control systems and machine learning methodologies to analyze and improve processes in non-traditional contexts. By systematically modeling burglary, it becomes possible to derive actionable insights that may inform better security measures. This innovative perspective contributes to the fields of engineering and criminology, opening pathways for future interdisciplinary research.

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