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# Intelligent control systems for future smart grid initiatives in electric utilities using EDAS methodology

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**Abstract:** *In response to intense competition, the pulp and paper industry is striving for greater efficiency and cost reduction by aiming for a more flexible production schedule. Moreover, the industry is prioritizing meeting global market demands for higher product quality, including more specialized items, while also enhancing productivity and environmental sustainability. Consequently, extensive research has been conducted to improve existing processes, with a growing focus on utilizing intelligent systems to control and optimize operations, presenting an appealing alternative for industry advancement. In a substation context, unlike traditional electrical equipment failures, malfunctions in Ethernet-style cyber components can disrupt operations, emphasizing the need for reliability. Selecting the appropriate Supervisory Control and Data Acquisition (SAS) package can mitigate the risk of widespread computer failures, ensuring compatibility across different vendors through the IEC-61850 protocol. This protocol has facilitated interoperability among SAS components, enabling a diverse range of manufacturers to contribute to the system's reliability. The naming conventions for neural networks and their characteristics vary. They typically involve rows and columns. Simple illustrations might include control scenarios, while applications are often tailored to specific systems in advance. Advanced humanoid robots, frequently employed for control tasks, embody human-like intelligence in robotics through algorithmic frameworks. They integrate fundamental control principles and strive to incorporate innovative concepts, reflecting ongoing efforts in the field of robotics. Upgrading the current traffic light system is made convenient by adopting an economic approach to infrastructure enhancement. A control system is established through an intermediate hardware device. This device serves as the signal controller, receiving input from the hardware and executing real-time operations accordingly. It effectively manages traffic light signals, addressing any violations and optimizing control through integrated hardware and software toolboxes within the device. This paper presents optional alternatives, which are assessed according to their deviation from the average solution. The mean solution, calculated through arithmetic mean, serves as the benchmark. The EDAS method, characterized by randomness, determines the mean solution. Proficiency in problem-solving is essential for implementing this method. Each criterion in the paper evaluates the performance of alternatives, assuming a normal distribution. To address these issues, a reliable EDAS method is introduced. This study introduces a hybrid method, combining Multi-Criteria Decision Making (MCTM) approaches with the proposed method. It addresses various criteria involved in decision-making processes. While MCTM methods are acknowledged for their quality, the thesis presents a hybrid solution. The research focuses on resolving material selection challenges in industrial applications through the Employment of Distance-based Assessment (EDAS). The methodology involves employing Design of Experiments (DOE) and EDAS to identify crucial material selection criteria and align them with the corresponding contexts. This process utilizes polynomial fitting to experimental data within multiple linear regression analysis. Burning zone temperature is got the first rank whereas is the Cold-end temperature is having the Lowest rank.*

**Keywords:** *LMD temperature, Cold-end temperature, Hot-end temperature, Burning zone temperature and Cold-end pressure*

# 1. INTRODUCTION

Perhaps a convenient explanation lies in the intellectual realm where control systems operate automatically. Control Systems and Artificial Intelligence intersect in describing various intelligent activities. Artificial intelligence research often revolves around activities involving control problems. Conversely, there's a keen interest among control engineers and researchers in adaptive learning control, aiming to design controllers that mimic human-like behaviors. This intersection of disciplines has sparked significant interest, particularly among control engineers, serving as a catalyst for further research and exchange in this burgeoning field [1]. For industrial applications involving intelligent controllers, it's essential to prioritize their development and implementation right from the outset of acquisition. This chapter serves as evidence for those involved, highlighting the immense intellectual challenge of condensing the vast field of control and variable systems into a single chapter. Rather than delving into exhaustive details, the focus here is on providing key ideas crucial for industry application. Examples illustrating the practical use of these methods are included for deeper understanding, along with references for further exploration. The chapter begins by introducing popular forms of intelligent control, such as fuzzy control, followed by discussions on neural networks, expert systems, planning systems, and genetic algorithms. Additionally, it touches on complex systems like autonomous control, all aimed at achieving sophisticated behaviors efficiently within industrial contexts [2]. The kiln process occurs naturally and involves numerous interconnected variables that must be carefully managed during operation. Various control measures need to be implemented to address these factors, which can fluctuate over time due to changing conditions. Additionally, certain measurements may be inconsistent, and the kiln's characteristics can evolve over extended periods, potentially affecting its performance. Disturbances such as alterations in the lime mud mixture or changes in properties can disrupt kiln operation. Therefore, maintaining safe and effective operation requires keeping specific process variables within predefined constraints to safeguard the environment [3]. The setup of SAS on a PC or workstation typically involves initial configuration offline, followed by storage in EPROMS. This configuration can be scheduled or performed directly. The SAS is then loaded into master or I/O units. This process marks the first automation of the substation. To gather operational data, emphasis is placed on parameters such as voltage, current, and device status sent to the NCC. While this transitional state allows for displaying this data, offering a current functional overview and snapshot of operational status, it does not offer a comprehensive system overview [4]. In the realm of trade control and optimization, two basic illustrations are provided. The initial instance involves a neural network structure termed the two-layer discrete-time model. This model is designed to construct a control system inadvertently. To enhance dependability and separation, bilateral associative memory can be employed. The second instance pertains to analog-to-digital conversion enhancement through the utilization of a single-layer continuous-time network [5]. To stimulate research interest in this field, the primary drivers are quite apparent. Humanoid robots are increasingly integrated into our daily lives, aiding in tasks ranging from assisting with operations to undertaking hazardous activities, thus assuming roles akin to key human workers. This shift towards anthropomorphic robots, capable of emulating human actions and navigating unstructured environments effectively, presents an intriguing prospect. Specifically, service robotics, medicinal applications, and hazardous environment operations emerge as crucial areas of focus. The development of advanced technologies in sensor, actuator, computing design, and manufacturing, particularly in the realm of humanoid robots, further propels research growth. Additionally, the reflective aspect of research units serves as another significant catalyst for the expansion of this field [6]. In the realm of urban traffic management, the efficiency of operations greatly hinges on effectively addressing congestion and traffic through signal control systems. These systems are crucial in alleviating vulnerabilities associated with traffic. There are two main classifications of control schemes: non-adaptive and adaptive. The primary disparity between these lies in their capability to dynamically adjust signal parameters in response to detected traffic conditions in real-time. Both non-adaptive and adaptive control systems aim to enhance system performance. Adaptive systems, however, demonstrate superior adaptability by promptly adjusting signal parameters based on real-time traffic data. Pavement loop detectors and on-street detectors, such as Vehicle-Actuated (VA) control system loop detectors, are commonly employed in adaptive systems. These technologies, frequently utilized in European countries, contribute significantly to the effectiveness of adaptive signal control settings [7]. The calcination process involves intricate dynamics and multiple variables, including nonlinear reactive kinetics, significant time lags, and variations in calcareous soil properties. Operating a lime kiln smoothly necessitates careful consideration and control of various interrelated factors. Numerous actions are required during operation, often requiring well-designed connecting components to adapt to fluctuating conditions. Additionally, some measurements may be unreliable, and the characteristics of the kiln can evolve over time [8]. Many researchers and educators in the field of fuzzy control systems advocate for the consistent incorporation of fuzzy constraints into mathematical models, a departure from traditional design methodologies. This shift, they argue, yields a more comprehensive understanding of the system. By utilizing mathematical models, which represent a wealth of knowledge, one can effectively construct and optimize control systems. For instance, simulations based on these models can be employed to further enrich the knowledge base. Moreover, leveraging the expertise of operators allows for the formulation of linguistic or semi-linguistic IF-THEN rules, a fundamental component of fuzzy control systems. Employing these strategies during the design phase maximizes the utilization of available information and enhances the overall effectiveness of the system [9]. The initial aspect concerns the non-linear nature of the Behavioral Locally Linear Model Tree (LoLiMoT) learning algorithm, which mirrors the neural processes in the brain, particularly focusing on emotional learning, as exemplified by the Zen Controller (BELBIC). This controller operates akin to a neuro fuzzy system, incorporating elements of a PID-type system, specifically designed for plant applications. However, employing this approach for temperature profile tracking presents challenges. Comparative analysis with a traditional PID controller through simulation demonstrates superior performance of BELBIC [10]. Expert Systems (ESs), Fuzzy Logic (FL), Neural Networks (NNs), and genetic algorithms (GAs) are among the cutting-edge Artificial Intelligence (AI) techniques currently employed in motor drive applications. The goal of AI is to replicate human or natural intelligence within computer systems, enabling them to think and make decisions akin to humans. Embedded Computational Intelligence refers to systems equipped with learning, self-organizing, or self-adaptive capabilities, essentially constituting intelligent controllers. These systems utilize advanced computational intelligence methodologies to effectively address intricate control challenges through a systematic and iterative process [11]. So far, there isn't a unified theory. The control of robots, particularly the acrobat, is quite complex. It involves managing two different dynamics types, which aren't linear. This complexity has led researchers to employ two distinct controllers: one for swinging up and another for maintaining balance. Typically, a heuristic approach is taken, involving strategies to guide the acrobat to reach a vertical position with zero velocity at its links [12]. Aquaponics represents a contemporary approach to farming, blending aquaculture and hydroponics seamlessly. In this innovative system, the synergy between fish farming and plant cultivation eliminates the need for traditional fertilizers. The water circulated between the fish tanks and the plant beds ensures that both thrive without requiring frequent adjustments. This harmonious setup fosters a mutually beneficial relationship among the fish, plants, and microorganisms, promoting ecological balance and sustainable food production. In essence, aquaponics offers a practical solution for producing nutritious food in a way that supports long-term environmental health [13]. Intelligent systems in residential buildings are crucial due to the high demand for control mechanisms. The significance lies in their ability to maximize energy savings, harness external environmental conditions optimally, and ensure the facility's proper maintenance. These objectives are influenced by two key factors: user preferences and external climatic conditions [14]. The conditions for operating micro grids involve their connectivity to the main power grid and their ability to function independently. Micro grids can either be connected to the mains grid or operate in isolation from it. The control and management of micro grids require sophisticated energy management systems, including computer-based controls. These systems ensure stability, maintain voltage quality, regulate active and reactive power flow, detect islanding events, synchronize phases, and handle various operational tasks such as recovery procedures [15].

## 2. MATERIALS AND METHOD

**LMD temperature:** Laser metal deposition (LMD) is a method of additive manufacturing where a laser beam generates a molten pool on a metal substrate. Powder is then introduced into this pool, melting and fusing with the substrate to form a bonded deposit. The desired geometry is achieved as layers are built up incrementally during the process.

**Cold-end temperature:** The average temperature at the cold-end of the operating air preheater is determined by the combination of the combustion air inlet temperature and the flue gas outlet temperature, which results in a value divisible by two. This average cold-end temperature is typically utilized when evaluating potential issues and plays a crucial role in determining the appropriate size and construction materials for the air preheater.

**Hot-end temperature:** The heater becomes hotter accordingly. Speed is directly proportional. It can be expelled, which is not surprising. Moreover, this correlation spans from 170°C to 260°C. Testing can be conducted within this range. The relationship appears to be highly linear within this scope, albeit with some slight unpredictability regarding PLA. The term 'hot-end' denotes the temperature of the hot end.

**Burning zone temperature:** Also referred to as the firing zone, the burning zone is located at the bottom part of the furnace, where the temperature ranges between 1300-1450°C (2372-2642°F), facilitating the formation of clinker. Monitoring and maintaining precise temperature levels are crucial for ensuring product quality, environmental considerations, as well as optimizing efficiency and extending the kiln's lifespan.

**Cold-end pressure:** Cold-end pressure typically refers to the pressure measured at the outlet or discharge side of a system, often a refrigeration or air conditioning system. In such systems, the pressure at the cold end signifies the pressure level after the refrigerant has passed through the evaporator or cooling component, where it absorbs heat from the surroundings. This pressure is crucial for assessing the efficiency and proper functioning of the cooling system.

**On-line measurements:** In online measurement, the sample is generated through a diversionary flow, taken away from the main process, and can potentially be reintroduced into the bioreactor. Sampling via process sensors allows for automatic measurement within this diverted flow.

**Laboratory analysis:** Laboratory analysis involves detecting pathogens, identifying human body tissues, and examining biological fluids for abnormalities. A variety of techniques such as chromatography, spectroscopy, mass spectrometry, microscopy, particle size analysis, physical characterization, physic chemistry methods, surface analysis, and various chemical tests are employed for this purpose. These tests provide a comprehensive assessment of deviations and changes, aiding in diagnostic and analytical applications.

**Controlled variables:** A control variable, within a research context, remains consistent throughout the study. While it may not be the primary focus of investigation, it's carefully managed as it could influence outcomes. For instance, in an experiment, regulating temperature ensures consistency. Other examples include standardizing types of glassware, maintaining fixed levels of humidity, or controlling the duration of testing. Similarly, controlling variables like the amount of light used ensures reliability in the results.

**Manipulated variables:** The variable being tested by the scientist is known as the manipulated variable. In this particular experiment, the scientist is measuring the impact of water on plant growth, making the amount of water the manipulated variable. It's important to note that an experiment typically focuses on one manipulated variable at a time.

**EDAS Method:** The concept of addressing multi-criteria problems within fuzzy environments is further developed through the extension of the EDAS method to the IVIF EDAS model. This enhancement allows for a comprehensive analysis without additional effort, as evidenced by previous research in the field of Etcher studies. The suggested approach proves to be particularly applicable in evaluating options related to e-waste or solid waste disposal technologies, disposal site selection, and other alternatives aimed at environmental protection. Specifically, it facilitates the comparison of hazardous material disposal technologies, streamlining decision-making processes in this critical domain [16]. The significance of the normal distribution lies in its prevalence and the predictable characteristics it offers. This distribution is widely encountered in various fields due to its symmetric bell-shaped curve, where the mean, median, and mode are all centrally located, reflecting a balanced distribution of data. It's important to note that the normal distribution does not consider skewness in the data, thus simplifying analysis. In addressing Multiple Criteria Decision Making (MCDM) problems, the EDAS method, a stochastic approach, has gained attention. It avoids unnecessary complexities and rigid assumptions. However, while EDAS is effective in certain scenarios, its reliance on the normal distribution might pose limitations, particularly in cases where the data exhibits skewness. A proposed extension in the paper suggests an innovative approach to tackle MCDM problems using the EDAS method. Although the normal distribution is commonly used, its inability to accommodate skewed data could be a drawback in this context. This highlights the importance of considering alternative methods or adaptations to effectively address the challenges posed by non-normal distributions in MCDM problems [17]. Various firms face diverse selection challenges, prompting the proposition of Multi-Criteria Decision Making (MCDM) methods. Among these methods, MACBETH and EDAS stand out, as they are applied across various domains in existing literature. This paper aims to integrate these two methods, marking the first attempt to do so [18]. In this genre-specific evaluation, known as MACBETH (Measuring Attractiveness by Technique) alongside EDAS (distance from average solution), a combined approach is employed. MACBETH provides a weighted scale for assessment, while EDAS ranks substitutes. Through this integration, the optimal steam boiler alternative for the textile company's dye room is determined [19]. The Analytical Hierarchy Process (AHP), developed by Thomas Satya, is a method for measuring through pairwise comparisons. It facilitates the determination of priority levels based on expert opinions. AHP aids in identifying relevant facts and their interconnections, allowing for a structured approach to problem-solving. This method involves breaking down the problem into its components, starting from the overarching objective, then evaluating criteria, sub-criteria, and potential solutions [20]. Numerous options exist to fulfill specific end-use needs, making the selection of the appropriate cotton fabric a challenging endeavor. Typically, this decision involves navigating conflicting factors and finding the optimal choice based on physical attributes. The process of grading and selecting cotton fabrics relies on evaluating various physical properties, which often leads to a complex decision-making scenario with conflicting criteria [21]. The novel EDAS system created in 2015 represents a fresh approach. When assessing alternatives, this method presupposes an average criterion solution. In this study, the EDAS method will be employed to select a sewing machine for a textile workshop. A significant aim of this research is to introduce the EDAS system into Turkish literature [22]. The situation involves applying the principles of mathematical analysis, particularly employing the Mean Solution (EDAS) method, to evaluate a problem using a Multi-Criteria Decision Making (MCDM) approach. The focus is on examining agricultural conditions within a specific locality, particularly regarding water management in crops. This evaluation encompasses consideration of multiple parameters related to agriculture. Selecting materials is crucial in product design and development, particularly in human manufacturing. The rapid advancements in manufacturing technology over the years have presented engineers with numerous options, necessitating careful consideration. Opting for the appropriate materials offers various advantages, including enhanced reliability and quality, cost reduction, and prolonged product lifespan [23]. In this and preceding investigations, the distinction lies in the extent to which a specific range of values is employed for assessing the coupling between criteria, aiding decision-makers in their selection process. The utilization of the EDAS weighting method necessitates consideration of scale dependency. Furthermore, this research incorporates various criteria such as report card scores, attendance, structure, achievement, and personality values, which are averaged to derive a comprehensive assessment [24]. Aside from primary factors, the remainder of the document is structured into four parts. The second segment, labeled as "CRITIC," offers an overview of the methodology and introduces the enhanced EDAS-M approach with thorough elaboration. The methodology encompasses both a broad overview and a detailed explanation of the extended EDAS-M method. Moving on to the third section, it focuses on the numerical validation of the proposed method. This section meticulously outlines all computations, each based on the established guidelines, and presents them sequentially with step-by-step instructions [25]. In both individual and group decision-making within an organization facing challenges in today's competitive market, effective strategies for supplier selection play a crucial role. With the aim of maintaining clarity on objectives, this paper proposes a systematic approach. Initially, it outlines six primary criteria, with efforts directed towards uncovering and elucidating each one through Importance-Performance Relationship Networks (IRNs). Furthermore, supplier performance is evaluated alongside the relative significance of these criteria. To refine the process, the perspectives of four experts are solicited to determine the weights assigned to these criteria using the IRN-Preference Ranking Organization Method for Enrichment Evaluations (IRN-PWM). Following this, the criteria are rigorously assessed and debated, leading to the ranking of suppliers using the IRN-Elimination and Choice Translating Reality (IRN-EDAS) method, from most favorable to least favorable [26]. The suggested method offers several benefits. Firstly, it addresses the issue of ambiguity often encountered in current EDAS methods. It also provides alternative approaches for influencing decision makers and expressing preferences. This method allows for greater control over decision-making processes. For instance, the extended obfuscation IVIF EDAS, a variation of EDAS, allows for manipulation of member and non-member degrees within a defined range, ensuring that the sum of endpoints equals 1. This facilitates the adjustment of decision maker controls and preferences expression [27]. Ensuring the continual and responsible expansion of a company involves prioritizing both its longevity and sustainable progress. This means not just pursuing growth for growth's sake, but also enhancing the market conditions in which it operates. It's crucial to focus on steady profit growth and bolstering capabilities while also staying attuned to competitive dynamics and opportunities for future expansion. This holistic approach is key to fostering a thriving business ecosystem [28]. This study, inspired by the benefits of Multiple Attribute Group Decision Making (MAGDM), enhances the conventional EDAS approach. Initially, various operators are employed to generate and visualize ambiguous data. Subsequently, a technique is introduced for decision makers to ascertain weights and optimize a model for attribute weight determination. Finally, a novel approach within the framework of the EADS system is devised to address the MAGDM issue, focusing on conceptually ambiguous scenarios [29]. Additionally, we aim to incorporate both subjective and objective information into a composite framework. We assign weights to these components and utilize the Euclidean Distance from Mean Solution (EDAS) approach to ensure unity. We employ measurement and level soft sets for assessment, utilizing a Single Valued Neutron sophism approach to tackle soft decision-making problems. We propose three distinct approaches for resolution. Finally, we demonstrate the effectiveness and feasibility of these approaches through a numerical example [30].

## 3. ANALYSIS AND DISCUSSION

**TABLE 1**. Intelligent Control System

| | On-line measurements | Laboratory analysis | Controlled variables | Manipulated variables |
|---|---|---|---|---|
| LMD temperature | 65.23 | 15.12 | 66.33 | 21.23 |
| Cold-end temperature | 10.20 | 16.12 | 99.66 | 11.31 |
| Hot-end temperature | 97.56 | 98.65 | 88.44 | 16.51 |
| Burning zone temperature | 65.28 | 96.23 | 22.11 | 14.71 |
| Cold-end pressure | 36.91 | 94.52 | 77.33 | 8.91 |
| **AVj** | **55.03600** | **64.12800** | **70.77400** | **14.53400** |

In the Intelligent Control System, employing the EDAS method, real-time measurements from various sensors are fed into the system. These measurements include temperatures at different points within the system, such as LMD temperature, cold-end temperature, hot-end temperature, and burning zone temperature, as well as cold-end pressure. These variables are then analyzed in the laboratory to ensure accuracy. The controlled variables, such as LMD temperature at 66.33, cold-end temperature at 99.66, hot-end temperature at 88.44, burning zone temperature at 22.11, and cold-end pressure at 77.33, are adjusted based on this analysis. Manipulated variables, like the AVj, are also determined and regulated accordingly, ensuring optimal system performance.

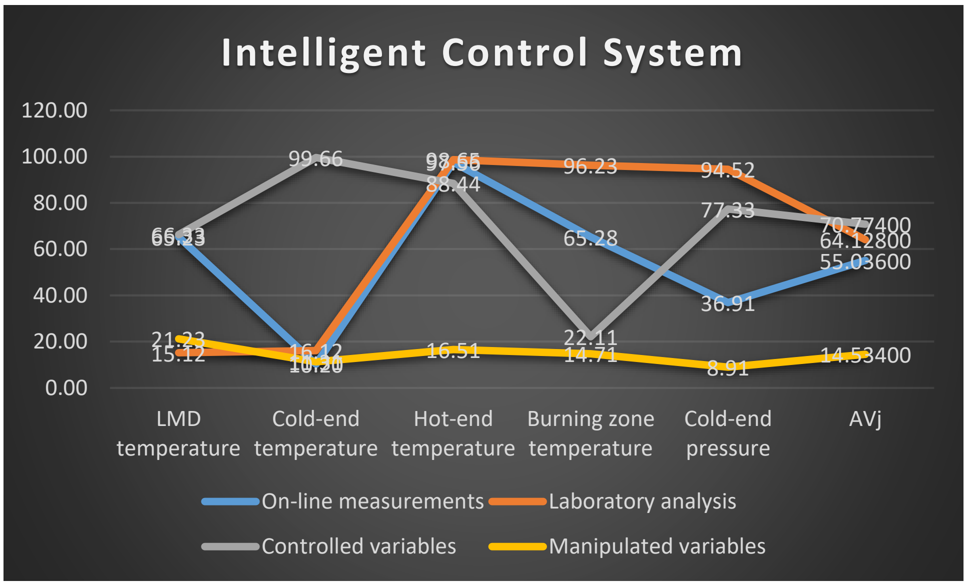


**FIGURE 1.** Intelligent Control System

In the Intelligent Control System utilizing the EDAS method, real-time data from on-line measurements is processed alongside laboratory analysis. These inputs inform the regulation of controlled variables like LMD temperature (66.33), cold-end temperature (99.66), hot-end temperature (88.44), burning zone temperature (22.11), and cold-end pressure (77.33). Manipulated variables, exemplified by AVj, are adjusted accordingly for optimal system performance.

**TABLE 2**. Positive Distance from Average (PDA)

| | **Positive Distance from Average (PDA)** | | | |
|---|---|---|---|---|
| LMD temperature | 0.19 | 0.00 | 0.06 | 0.00 |
| Cold-end temperature | 0.00 | 0.00 | 0.00 | 0.22 |
| Hot-end temperature | 0.77 | 0.54 | 0.00 | 0.00 |
| Burning zone temperature | 0.19 | 0.50 | 0.69 | 0.00 |
| Cold-end pressure | 0.00 | 0.47 | 0.00 | 0.39 |

Table 2 showcases the Positive Distance from Average (PDA) calculated through the EDAS method. PDA values depict the extent of deviation of each variable from its average. For instance, hot-end temperature exhibits notable deviations, suggesting potential areas for adjustment or intervention. By scrutinizing PDAs, the EDAS method facilitates targeted actions to enhance system performance and efficiency. LMD temperature, Cold-end temperature, Hot-end temperature, Burning zone temperature and Cold-end pressure. On-line measurements, Laboratory Analysis, Controlled Variables and Manipulated variables is seen all Maximum Value.

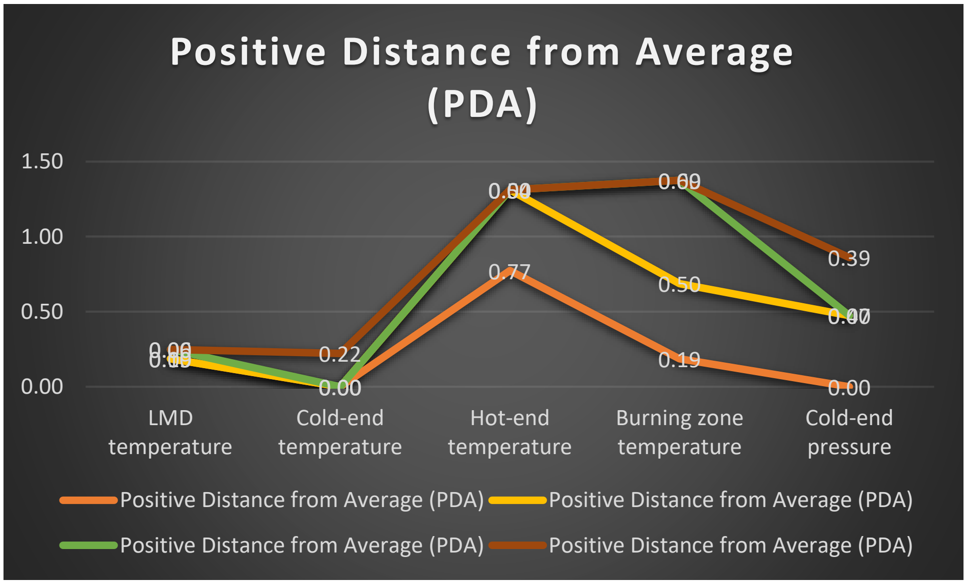


**FIGURE 2.** Positive Distance from Average (PDA)

Figure 2 illustrates the Positive Distance from Average (PDA) values derived using the EDAS method. These values indicate the extent of deviation of each variable from its respective average. Notably, the hot-end temperature exhibits substantial disparities, warranting attention for potential adjustments. Through the EDAS method, targeted interventions can be implemented based on PDA analysis, enhancing overall system performance and efficiency. LMD temperature, Cold-end temperature, Hot-end temperature, Burning zone temperature and Cold-end pressure. On-line measurements, Laboratory Analysis, Controlled Variables and Manipulated variables is seen all Maximum Value.

**TABLE 3**. Negative Distance from Average (NDA)

| | **Negative Distance from Average (NDA)** | | | |
|---|---|---|---|---|
| LMD temperature | 0.00000 | 0.76422 | 0.00000 | 0.46071 |
| Cold-end temperature | 0.81467 | 0.74863 | 0.40814 | 0.00000 |
| Hot-end temperature | 0.00000 | 0.00000 | 0.24961 | 0.13596 |
| Burning zone temperature | 0.00000 | 0.00000 | 0.00000 | 0.01211 |
| Cold-end pressure | 0.32935 | 0.00000 | 0.09263 | 0.00000 |

Table 3 depicts the Negative Distance from Average (NDA) values calculated using the EDAS method. NDA values represent how far each variable falls below its average. For instance, the cold-end temperature exhibits notable negative distances, indicating areas for potential improvement or adjustment. By analyzing NDA values, the EDAS method enables targeted interventions to optimize system performance and efficiency effectively. LMD temperature, Cold-end temperature, Hot-end temperature, Burning zone temperature and Cold-end pressure. On-line measurements, Laboratory Analysis, Controlled Variables and Manipulated variables is seen all Maximum Value.

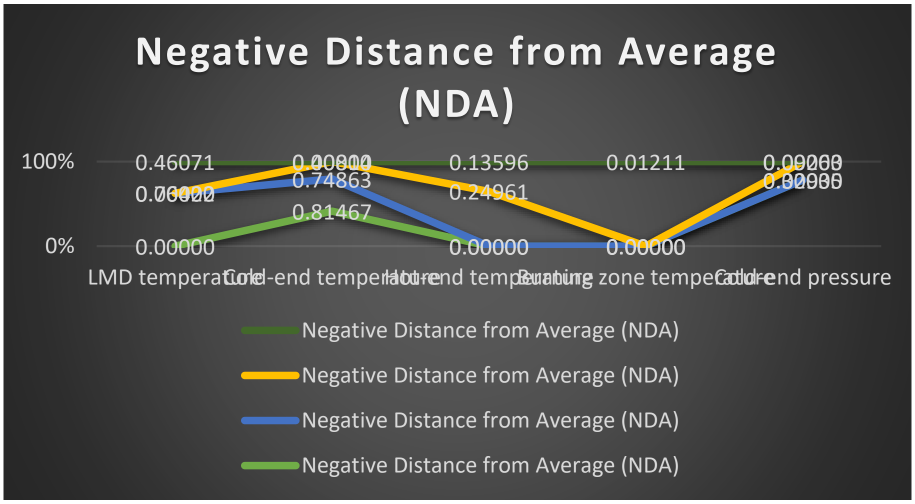


**FIGURE 3.** Negative Distance from Average (NDA)

Figure 3 illustrates the Negative Distance from Average (NDA) values computed using the EDAS method. These values indicate how much each variable falls below its respective average. Notably, the cold-end temperature demonstrates significant negative distances, suggesting areas for potential enhancement or adjustment. Through NDA analysis facilitated by the EDAS method, targeted interventions can be implemented to optimize system performance effectively. LMD temperature, Cold-end temperature, Hot-end temperature, Burning zone temperature and Cold-end pressure. On-line measurements, Laboratory Analysis, Controlled Variables and Manipulated variables is seen all Maximum Value.

**TABLE 4**. weightages

| Weightages | | | |
|---|---|---|---|
| 0.25 | 0.25 | 0.25 | 0.25 |
| 0.25 | 0.25 | 0.25 | 0.25 |
| 0.25 | 0.25 | 0.25 | 0.25 |
| 0.25 | 0.25 | 0.25 | 0.25 |
| 0.25 | 0.25 | 0.25 | 0.25 |

Table 4 presents the weightages utilized within the EDAS method. Each variable is assigned equal weightage, denoted by 0.25 across all categories. This uniform distribution ensures an unbiased evaluation of variables, promoting fairness and consistency in the decision-making process. By employing standardized weightages, the EDAS method facilitates systematic and transparent analysis, enhancing the reliability of outcomes and recommendations.

**TABLE 5.** Weighted PDA SPi

| Weighted PDA | | | | SPi |
|---|---|---|---|---|
| 0.04631 | 0.00000 | 0.01570 | 0.00000 | 0.06200 |
| 0.00000 | 0.00000 | 0.00000 | 0.05546 | 0.05546 |
| 0.19316 | 0.13458 | 0.00000 | 0.00000 | 0.32775 |
| 0.04653 | 0.12515 | 0.17190 | 0.00000 | 0.34358 |
| 0.00000 | 0.11848 | 0.00000 | 0.09674 | 0.21522 |

Table 5 displays the Weighted Positive Distance from Average (PDA) values, denoted as SPi, calculated using the EDAS method. These values represent the weighted deviation of each variable from its average, indicating their relative importance in the decision-making process. By assigning appropriate weights, the EDAS method ensures that variables with greater significance contribute more substantially to the overall analysis, leading to more informed and balanced decisions.

**TABLE 6.** Weighted PDA SPi

| Weighted NDA | | | | SNi |
|---|---|---|---|---|
| 0.00000 | 0.19106 | 0.00000 | 0.11518 | 0.30623 |
| 0.20367 | 0.18716 | 0.10204 | 0.00000 | 0.49286 |
| 0.00000 | 0.00000 | 0.06240 | 0.03399 | 0.09639 |
| 0.00000 | 0.00000 | 0.00000 | 0.00303 | 0.00303 |
| 0.08234 | 0.00000 | 0.02316 | 0.00000 | 0.10550 |

Table 6 presents the Weighted Negative Distance from Average (NDA) values, represented as SNi, computed through the EDAS method. These values reflect the weighted extent to which each variable falls below its average, indicating their respective contributions to the decision-making process. By assigning appropriate weights, the EDAS method ensures that variables with greater significance are prioritized, facilitating more accurate and comprehensive analyses.

**TABLE 7.** Final Result of Intelligent Control System

| | NSPi | NSPi | ASi | Rank |
|---|---|---|---|---|
| LMD temperature | 0.18046 | 0.37866 | 0.27956 | **4** |
| Cold-end temperature | 0.16141 | 0.00000 | 0.08070 | **5** |
| Hot-end temperature | 0.95392 | 0.80442 | 0.87917 | **2** |
| Burning zone temperature | 1.00000 | 0.99386 | 0.99693 | **1** |
| Cold-end pressure | 0.62640 | 0.78595 | 0.70618 | **3** |

Table 7 showcases the final results of the Intelligent Control System using the EDAS method. Each variable is evaluated based on three criteria: NSPi, NSPi, and ASi. These criteria contribute to the ranking of variables, with the Burning zone temperature securing the top position, followed by Hot-end temperature. The rankings provide insights into the effectiveness of variable control within the system. NSPi in Entrepreneurs is calculated using the Burning zone temperature is having is Higher Value and Cold-end temperature is having Lower value. NSPi in calculated using the Burning zone temperature is having is Higher Value and Cold-end temperature is having Lower value. ASi in calculated using the Burning zone temperature is having is Higher Value and Cold-end temperature is having Lower value.

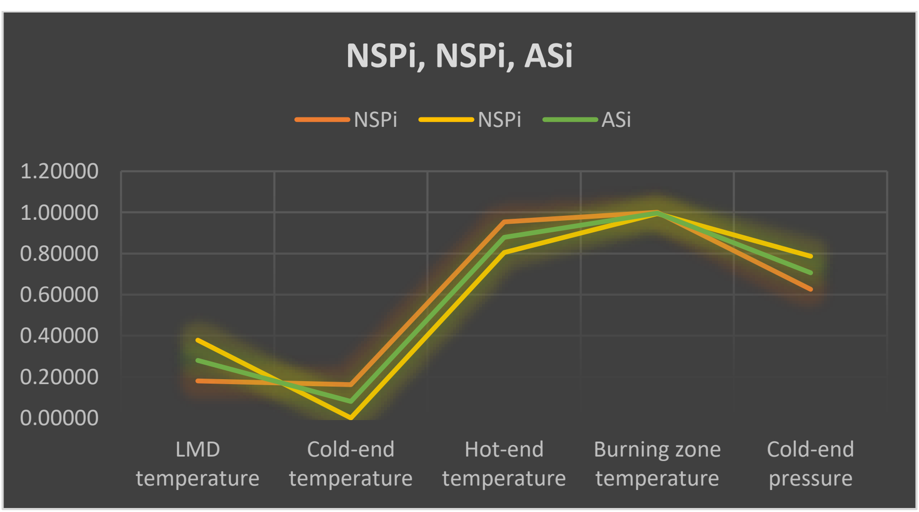


**FIGURE 4.** Final Result of Intelligent Control System

Figure 4 illustrates the final results of the Intelligent Control System employing the EDAS method. Each variable is assessed based on NSPi, NSPi, and ASi criteria, contributing to its overall ranking. The Burning zone temperature attains the highest rank, followed by Hot-end temperature, showcasing their effectiveness within the system. These rankings offer valuable insights for optimizing control strategies and system performance. NSPi in Entrepreneurs is calculated using the Burning zone temperature is having is Higher Value and Cold-end temperature is having Lower value. NSPi in calculated using the Burning zone temperature is having is Higher Value and Cold-end temperature is having Lower value. ASi in calculated using the Burning zone temperature is having is Higher Value and Cold-end temperature is having Lower value.

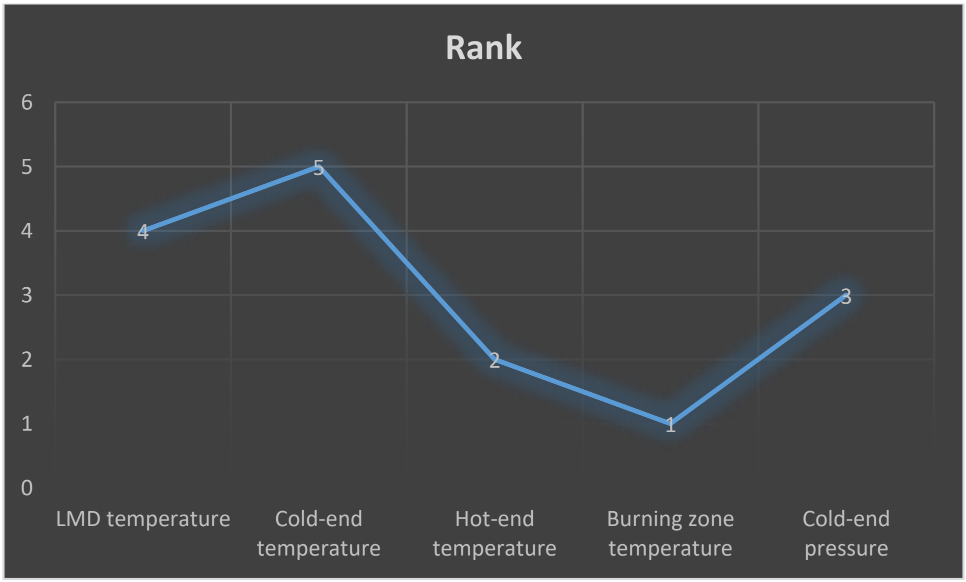


**FIGURE 5.** Shown the Rank

Figure 5 displays the rankings assigned to each variable within the Intelligent Control System utilizing the EDAS method. The Burning zone temperature secures the top position with a rank of 1, followed by Hot-end temperature at rank 2. Cold-end pressure occupies rank 3, while LMD temperature and Cold-end temperature hold ranks 4 and 5, respectively. These rankings offer valuable insights into variable effectiveness. Burning zone temperature is got the first rank whereas is the Cold-end temperature is having the Lowest rank.

## 4. CONCLUSION

Artificial intelligence research often revolves around activities involving control problems. Conversely, there's a keen interest among control engineers and researchers in adaptive learning control, aiming to design controllers that mimic human-like behaviors. This chapter serves as evidence for those involved, highlighting the immense intellectual challenge of condensing the vast field of control and variable systems into a single chapter. Rather than delving into exhaustive details, the focus here is on providing key ideas crucial for industry application. This configuration can be scheduled or performed directly. The SAS is then loaded into master or I/O units. This process marks the first automation of the substation. To gather operational data, emphasis is placed on parameters such as voltage, current, and device status sent to the NCC. The initial instance involves a neural network structure termed the two-layer discrete-time model. This model is designed to construct a control system inadvertently. To enhance dependability and separation, bilateral associative memory can be employed. The second instance pertains to analog-to-digital conversion enhancement through the utilization of a single-layer continuous-time network. This shift, they argue, yields a more comprehensive understanding of the system. By utilizing mathematical models, which represent a wealth of knowledge, one can effectively construct and optimize control systems. For instance, simulations based on these models can be employed to further enrich the knowledge base. It involves managing two different dynamics types, which aren't linear. This complexity has led researchers to employ two distinct controllers: one for swinging up and another for maintaining balance. Typically, a heuristic approach is taken, involving strategies to guide the acrobat to reach a vertical position with zero velocity at its links. The suggested approach proves to be particularly applicable in evaluating options related to e-waste or solid waste disposal technologies, disposal site selection, and other alternatives aimed at environmental protection. Specifically, it facilitates the comparison of hazardous material disposal technologies, streamlining decision-making processes in this critical domain. The Analytical Hierarchy Process (AHP), developed by Thomas Satya, is a method for measuring through pairwise comparisons. It facilitates the determination of priority levels based on expert opinions. AHP aids in identifying relevant facts and their interconnections, allowing for a structured approach to problem-solving. This method allows for greater control over decision-making processes. For instance, the extended obfuscation IVIF EDAS, a variation of EDAS, allows for manipulation of member and non-member degrees within a defined range, ensuring that the sum of endpoints equals 1. This facilitates the adjustment of decision maker controls and preferences expression. This study, inspired by the benefits of Multiple Attribute Group Decision Making (MAGDM), enhances the conventional EDAS approach. Initially, various operators are employed to generate and visualize ambiguous data. Subsequently, a technique is introduced for decision makers to ascertain weights and optimize a model for attribute weight determination.

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