Dynamic User Interfaces for Control Systems

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Abstract— **Control systems monitor and command other devices, systems, and software within an infrastructure. Typically, control systems employ human-in-the-loop control for critical decision making and response. These end-users require easy access to accurate, actionable and relevant data to ensure quick and effective decision making. This work presents a framework for creating dynamic visual interfaces for improved situational awareness. The proposed framework determines the relevance of available information pieces and then applies the derived relevance scores to a visualization so that the most relevant and important information are emphasized to the end-users. In the presented work, a priori expert knowledge is encoded in the system through the use of Fuzzy Logic (FL) and the resulting FL inference system assigns scores to information pieces based on system state information and user defined relevance. These scores can then be used to organize and display the relevant data given the current situation and end-user roles. The proposed FL based scoring system was implemented on a real world control system dataset and we demonstrate how the information visualization is dynamically adapted to improve situational awareness. Further, we discuss potential methods the relevance scores can be incorporated into real world visualizations to increase the situational awareness in control systems.**

Keywords—Fuzzy Logic, Control Systems, Dynamic Visualization

I. INTRODUCTION

Control systems integrate heterogeneous information from potentially large networks of physical devices and computational algorithms to measure, model, and control a system, or plant [1]. Typical control systems, such as critical infrastructure and cyber-physical systems, employ feedback loops that allow the system to dynamically adapt based on the various available inputs [2], [3]. Additionally, control systems often incorporate human-in-the-loop elements for critical-decision making and response during emergency situations. These controllers, or end-users, require data representations that are not only frequently updated and accurate, but also relevant [4]. However, the presentation of relevant information is not a trivial task. Since the relevance of information can be highly situational, the information needed to gain adequate system awareness for a specific user may only be a small subset of the entire system [5]. Due to the potentially large amounts of information available from the system, static information visualization can result in suboptimal situational awareness, which can lead to catastrophic failures.

Fuzzy logic is a well-documented and proven methodology for tasks involving weighted values [6]. The fuzzy weighted values can be used for various ranking and scoring tasks. In control systems, prior works have used fuzzy logic scoring and ranking systems for decision making in micro grids [7], controllers [8], anomaly detection [9], network weighting [10], [11], and detector scoring [12]. Fuzzy logic ranking and scoring systems have also been implemented for robot control [13], cancer treatment predictions [14], quality of experience modelling [15], fuzzy preference relations [16], and summarization methods [17].

This work presents a dynamic visual interface framework for improving the situational awareness in control systems. The framework involves two aspects: 1) Dynamic scoring of information pieces with respect to situational relevance and 2) Organizing and displaying the information such that the information relevance is apparent. A fuzzy logic inference system is presented for the scoring system, and several methods for data visualization that incorporate the resulting scores are explored.

Fuzzy logic inference was chosen because of its ability to embed imprecise expert knowledge in the form of "fuzzy rules". Thus, the scoring system can be created based on the descriptive "fuzzy" rules [18], [8]. The expert knowledge can include qualitative observations (when x is low, y is high) and system wide state information [13]. In addition to embedding the knowledge, end-user defined needs can be included as well in order to tailor the relevance scores to specific sub-systems with smaller scopes. Using a fuzzy rule set also has an advantage over other black-box modeling methods in that the rules are human understandable. This improves the interpretability of the system, which increases trustworthiness, reduce confusion, and makes tweaking the model an easier task. These rules can be modified based on the type of system and individual user roles, adding a level of generalization to the inference system.

The rest of the paper is organized as follows. Section II provides a brief introduction in fuzzy logic systems (FLS), Section III elaborates the presented FLS based dynamic visualization framework, Section IV discusses the experimental setup and the results obtained and finally Section V concludes the paper.

II. FUZZY LOGIC SYSTEMS

This section provides a brief overview of fuzzy logic systems and the inference procedure.

Fuzzy Logic Systems (FLS) are a well-documented method for control and data mining. Fuzzy logic is based on fuzzy set theory where an element can "partially" belong to multiple sets

Fig. 1: Cyber physical Directory [9]

with respect to a degree of membership as opposed to crisp set theory where an element belonging to a set is binary. The main advantage of FLS is its capability of incorporating human knowledge in terms of linguistic fuzzy rules. Further, FLS have the capability to handle imprecision, ambiguity and uncertainty.

In general, a FLS is comprised of four major components:1) Input fuzzification, 2) fuzzy rule base, 3) fuzzy inference engine and 4) output defuzzification. There are mainly two types of FLS: 1) Mamdani, 2) Takagi-Sugeno (TS). In this work, a TS type fuzzy system is implemented. As mentioned the FLS maintains a fuzzy rule base populated with fuzzy linguistic rules. A TS type fuzzy rule can be written as follows:

$$\text{Rule } R_k\text{: }\mathbf{IF}\ x_1\ is\ A_1^k\ \boldsymbol{AND}\ x_2\ is\ A_2^k \dots \boldsymbol{AND}\ x_n\ is\ A_n^k$$

$$\boldsymbol{THEN}\ y_k = f_k(x_1, x_2, \dots, x_n)$$

Here, A_i^k denote the i[th] input fuzzy set for the k[th] fuzzy rule and n is the dimensionality of the input vector $\vec{x}$. In TS type fuzzy systems, the output of a rule is a function. By using this type, output fuzzy sets do not need to be formulated through a priori knowledge. Once the rule base is defined in the given form, the degree of relevance for a rule is calculated using the minimum t-norm operation as follows:

$$\mu_{R_k}(\vec{x}) = \min_{i=1,\dots,n} \left\{\mu_{A_1^k}(x_i)\right\}$$

Here, $\mu_{R_k}(\vec{x})$ is the degree of firing of the k[th] fuzzy rule and $\mu_{A_1^k}(x_i)$ is the degree of membership of x_i to fuzzy set A_1^k.

The output is calculated for each rule using the output function multiplied by the degree of relevance. The combined output is calculated as the weighted average across all rules in the rule base. For a rule base with R rules, the final output can be calculated as follows:

$$y = \frac{\sum_{k=1}^{R} \mu_{R_k}(\vec{x}) f_k(x_1, x_2, \dots, x_n)}{\sum_{k=1}^{R} \mu_{R_k}(\vec{x})}$$

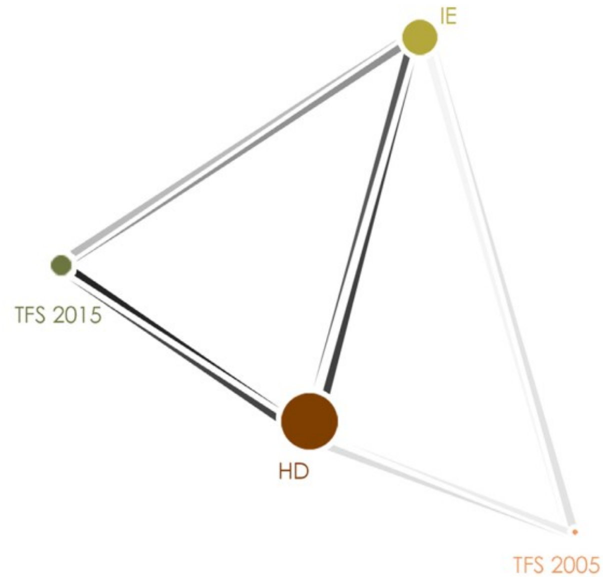

Fig. 2: Basic NLD Design [10]

III. Fuzzy Logic based Dynamic Visualization

This section discusses the presented fuzzy logic based dynamic visualization framework and different methods it can be used in real world control systems.

The first part of the proposed framework is the fuzzy logic scoring system. The system assigns a score to each available piece of information based on the information's relevance to the current state of the system. The scores are generated by implementing a fuzzy rule base that is created from accumulated expert knowledge of the control system. This expert knowledge can include qualitative understanding gained through observation, sensor data, and computational models such as state estimations, anomaly detection, and cyber-attack detection, anomaly detection. The fuzzy scoring system may also incorporate rules based on individual user knowledge and role requirements. Ultimately, the relevance scores should represent the specific needs of the end-user, and embedding user specific rules into the fuzzy system would allow for fine tuning in the scoring process. Once the fuzzy rule base is defined, system state information is input into the fuzzy system and the scores are calculated.

The derived relevance scores can then be applied to a visualization scheme to generate an optimized user interface. Three visualization techniques have been considered that could take advantage of the ranked information pieces. The first is a dynamic cyber-physical display directory that finds the optimal areas for each of the inputs based on their scores [19] [20]. The Cyber-Physical Directory uses linear programming optimization to scale information with a higher score to be larger than those with smaller scores while also maximizing the amount of the display area used. The physical directory design gathered user defined metrics (i.e. movie preferences) from smartphones in its vicinity and used the collected scores to present recommendations, using only the area to indicate which objects were more likely to be relevant to the user. (Figure 1) Since this design already requires a scoring system to function, using the

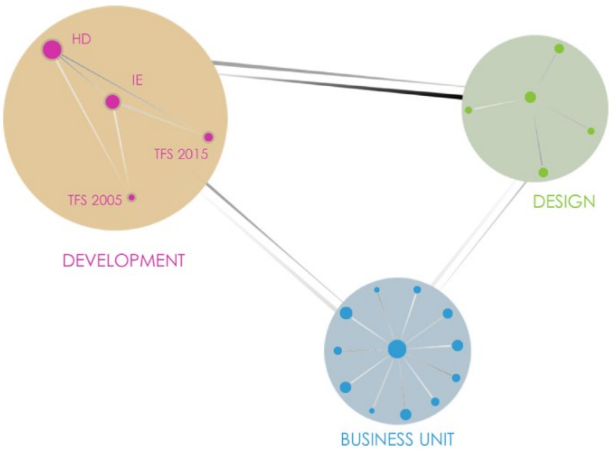

Fig 3: Hierarchical Balloon NLD Design [10]

fuzzy scoring system as the backend would generate a visual hierarchy of system information and allow the end-users to quickly and easily see which pieces of system information are the most important.

Another promising visualization method is Node Link Diagrams (NLD). [21] NLD layouts use a classic graphical representation that is intuitive, customizable, and can represent the entirety of the data flow across the system. These diagrams represent various entities as nodes in a tree structure with links showing relationships between entities. (Figure 2) Nodes are represented in the NLD by circles of various sizes and colors to quickly and intuitively identify information about the entities encapsulated in the node. Links are represented by unidirectional lines to show the directional flow of information. Links can also vary in density to show strong each connection is, with lighter links showing weaker relationships and darker links showing stronger relationships.

Since control systems can be very large in size, NLD visualizations can become convoluted and web-like reducing the overall intuitiveness of the design. To counter this, a balloon layout can be used. Balloon layouts allow nodes to represent subsystems of connected entities that are represented by another NLD within the node. (Figure 3) This helps keep the design simple and intuitive while also visually representing hierarchical dependencies within the control system. Due to the highly customizable design, relevance scores can be integrated to create dynamic NLDs to aid in the situational awareness of a system. The relevance score for each entity can be represented by showing only relevant nodes, modifying each node's area, changing the colors of the nodes, and altering the strength of the links. All of these elements can help provide a complete picture of the system scope an end-user is responsible for without unnecessary visual clutter, as well as guide them to the information they need to fulfill their role.

Many control systems use algorithms to identify threats and propose countermeasures to aid end-users in the decision making process. However, the various solutions are often presented with equal priority which may result in suboptimal risk mitigation. The Analytic Hierarchy Process (AHP) has been

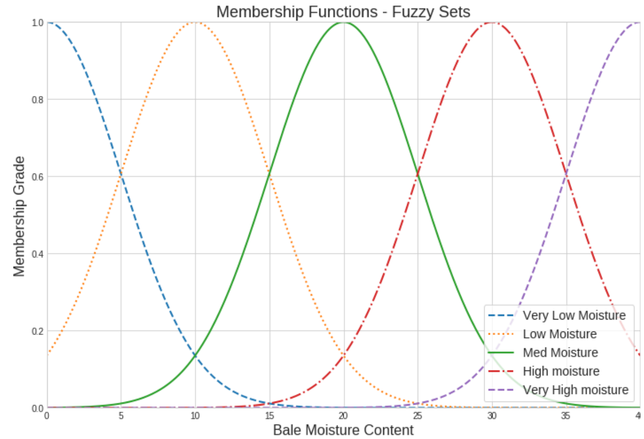

Fig 4: Fuzzy membership functions used for Bale Moisture Content

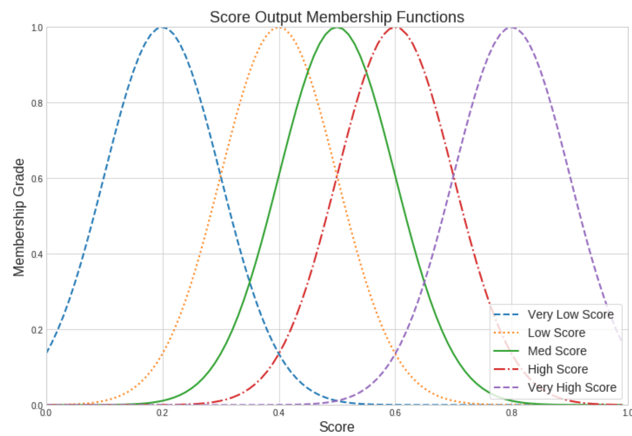

Fig 5: Fuzzy membership functions used for output relevance scores

shown to provide a solution to this problem by ranking potential countermeasures by effectiveness based on multiple predefined criteria. [22] The fuzzy scoring system could be used to dynamically rank and create the sets of criteria that need to be met. Scoring based on the current system state could ensure that the areas that are most affected during an emergency situation are solely addressed by removing excess noise from non-affected criteria during the AHP calculations. The fuzzy inference system could also use the predefined criteria as expert knowledge to help define the rule base. This would increase the specificity of the fuzzy system and could add another layer of information provided to the end-user. By displaying how relevant the solutions are for each of the criteria, end-users would gain increased situational awareness during critical risk management scenarios.

IV. Experimental Setup and Results

This section details the implementation and results for the fuzzy logic based information ranking system on a real world dataset.

The data used in this paper was collected by Idaho National Laboratory (INL) in Idaho Falls, Idaho using the Biofuels National User Facility Preprocessing Process Demonstration

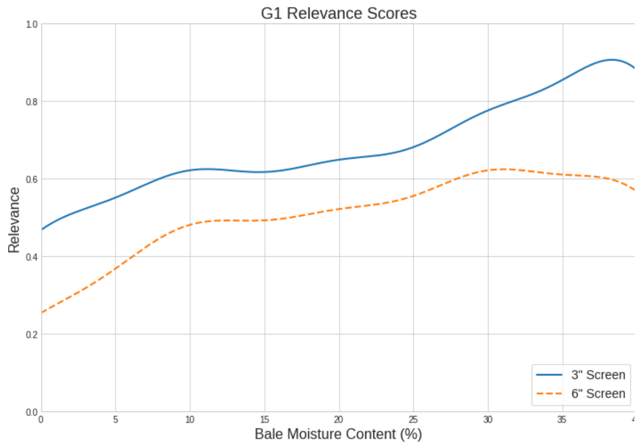

Fig 6: G_1 Relevance Score vs BMC

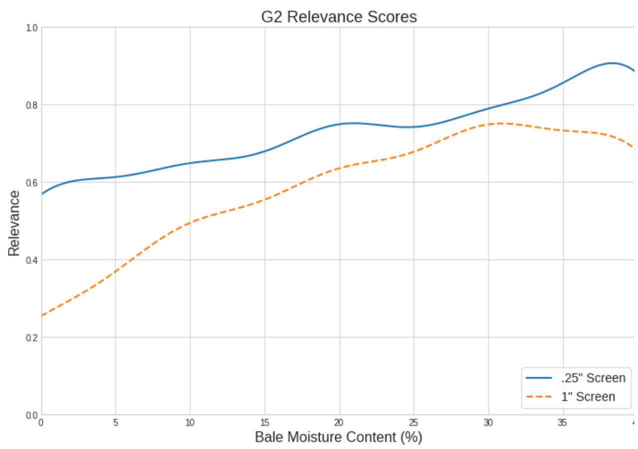

Fig 7: G_2 Relevance score vs BMC

Unit (PDU). The dataset contains attributes that describe the mechanical size reduction (comminution) process used during the biomass feedstock preprocessing phase for biofuel production. The PDU uses two sequential grinders in the comminution process (G_1 and G_2). Each grinder has interchangeable grinding screens of various sizes to reduce the biomass feedstock bales to predefined particle sizes. [23]

To ensure performance (i.e. throughput) and reliability (i.e. uptime), operators can change the infeed rate of the bales into the system and the screen sizes on the grinders. The selection of these parameters is mainly affected by the moisture content of the feedstock being fed into the PDU. The operators have access to real-time monitoring tools to allow them to gauge the health of the PDU. These tools can be difficult to navigate since there is a high volume of attributes the user interface is fed with. However, the relevance of the information is dependent of the control configuration. Therefore, to find the most relevant information the operator is required to navigate through an array of non-relevant information. This can result in time wasted searching for relevant and actionable information during which the system could fail. A potential solution would be to display all the data on a single screen, but due to the amount of information available this would result in a visually cluttered presentation that forces the operators to either memorize where each piece of information is located or scan the screen until they find what they need. Therefore, we present an information

TABLE I: FUZZY RULE BASE FOR G1 DATA RELEVANCE

Screen Size / BMC	3 Inch	6 Inch
Very Low	Low Relevance	Very Low Relevance
Low	Medium Relevance	Low Relevance
Medium	Medium Relevance	Low Relevance
High	High Relevance	Medium Relevance
Very High	Very High Relevance	Medium Relevance

TABLE II: FUZZY RULE BASE FOR G_2 DATA RELEVANCE

Screen Size / BMC	.25 Inch	1 Inch
Very Low	Medium Relevance	Very Low Relevance
Low	Medium Relevance	Low Relevance
Medium	High Relevance	Medium Relevance
High	High Relevance	High Relevance
Very High	Very High Relevance	High Relevance

TABLE III: RELEVANCE SCORE OUTPUTS* FOR PDU DATA

	G_1		G_2	
Screen Size / BMC	**3 Inch**	**6 Inch**	**0.25 Inch**	**1 Inch**
7.3%	0.59	-	-	0.43
9.1%	0.61	-	0.64	-
10.5%	0.62	-	0.65	-
11.2%	-	0.49	-	0.51
17.4%	-	0.50	-	0.60
20.6%	0.65	-	-	0.64
23.1%	-	0.54	-	0.66
28.5%	0.75	-	-	0.73
29.0%	-	0.61	-	0.74
37.2%	0.90	-	-	0.73

*Scores range from 0 to 1, where 0 is no relevance and 1 is the maximum relevance

scoring system that can be used to sort the information based on their relevance. This is a first step towards dynamic user interfaces for control where the information content shown will

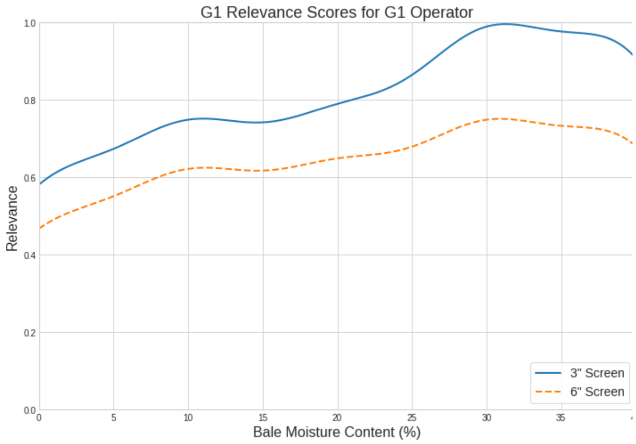

Fig 8: G_1 Relevance Score vs BMC using G_1 Operator Rule Base

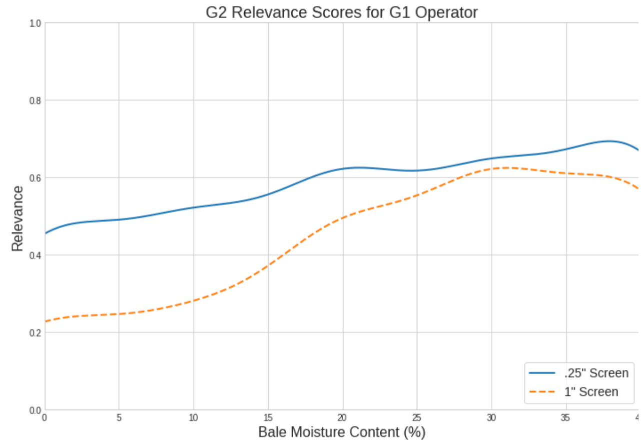

Fig 10: G_2 Relevance Score vs BMC using G_1 Operator Rule Base

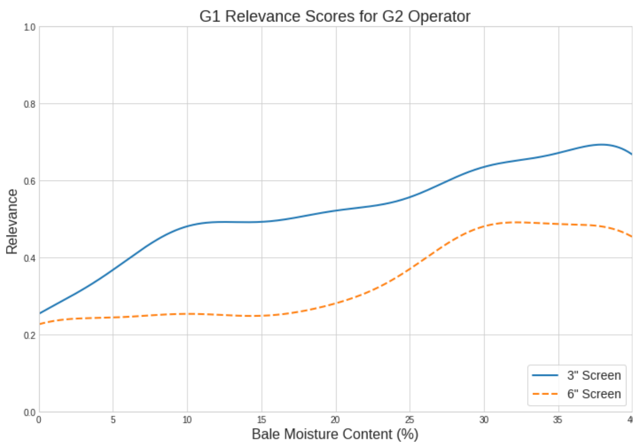

Fig 9: G_1 Relevance score vs BMC using G_2 Operator Rule Base

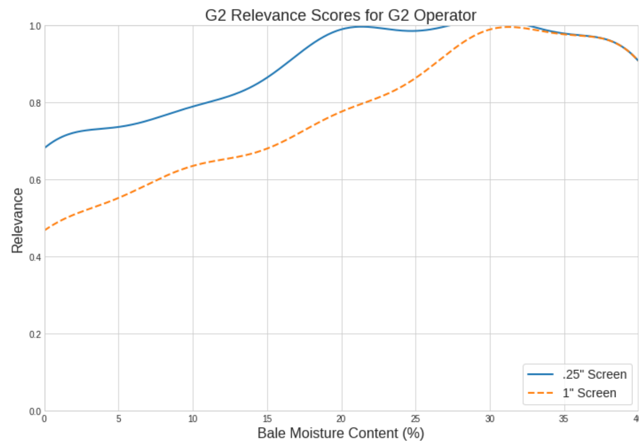

Fig 11: G_2 Relevance score vs BMC using G_2 Operator Rule Base

adapt to the situation giving the most relevant information to the operator immediately.

For better understandability and simplicity, the presented implementation demonstrates ranking of two of the information pieces available from the PDU system. The fuzzy scoring system outputs scores for each of the grinders with a higher score correlating to a higher relevance to the operator. Two inputs were used to generate the scores: the Bale Moisture Content (BMC) and the screen size on the grinder. Five Gaussian membership functions were used to represent very low, low, medium, high and very high bale moisture content (Figure 4). Similarly five Gaussian membership functions were used for the output relevance scores as well (Figure 5). Since the screen sizes are scalar values, they are represented with binary values rather than membership degrees. The fuzzy rule bases for the two grinders, shown in Table I and Table II, were derived using expert knowledge for how important an operator would consider the information from each grinder based on the given fuzzy inputs. The final output score is a value between 0 and 1, with 0 representing no relevance and 1 representing maximum relevance.

The fuzzy rule bases were created with the input of the control engineers who handle the PDU. Therefore, given different control scenarios, the relevance/importance of the information was ranked in linguistic terms embedding the knowledge of the experts. For instance, when the moisture content is high, most of the grinding process is carried out using the stage one grinder. Therefore, the operator needs to be closely monitoring stage 1 grinder and hence the rank of the stage 1 grinder information is set to “High”. Similarly, the rule base captures the expert knowledge for the different scenarios identified. In future work, it should be noted that these rules can be created using data driven methods as well. Thus, the rule base can be expanded automatically to complement the expert knowledge.

First, the degree of membership for the bale moisture content is found for each of the membership functions. Then for each rule, the membership degree is multiplied by the corresponding binary value for the screen size and a scalar value that represents the desired low, medium, or high score. For the presented implementation, values of 0.2, 0.4, 0.5, 0.6 and 0.8 were chosen to represent very low, low, medium, high, and very high information relevance respectively. The relevance score for each of the grinders is calculated by taking the average of all the singleton values output from the fuzzy rule base. A sample of scores output by the fuzzy scoring system on the PDU dataset is shown in Table III.

Figure 6 and figure 7 show the outputs of the fuzzy scoring system over a continuous set of bale moisture content inputs. Notably, the relevance scores correspond to the expert rules

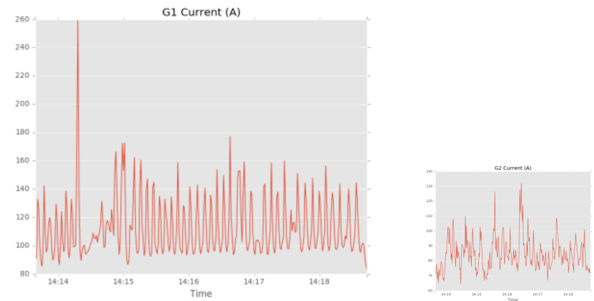

Fig 12: User Interface Example for High G1 Relevance

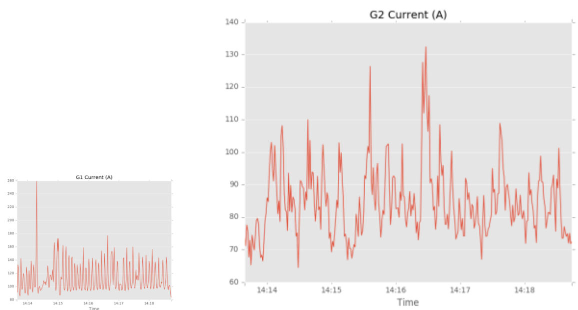

Fig 13: User Interface Example for High G2 Relevance

described in Table I and Table II. It can be seen that the relevance of the grinders varies depending on the screen size and the bale moisture content. Further, it can be seen that the relevance scores reflect the expert knowledge embedded in the system. For instance, when the bale moisture content is high, the operator should be paying attention to stage 1 grinder since it does most of the work. It can be seen that the G_1 score is high and G_2 score is low. Thus, when translated to a dynamic visualization, the operator will see more emphasis paid on G_1 than G_2.

Additionally, user-role specific rules are introduced to further increase the user specificity of the system. If there are operators assigned to each grinder, then an operator for G_1 might not need to see information from G_2, or only see it under specific circumstances. Figure 8 and figure 9 show the outputs using a modified rule base for an operator assigned to G_1. Since information from G_1 would be more relevant to the G_1 operator, the outputs for the G_1 rule base are raised one level. Similarly, the outputs for the G_2 rule base are lowered one level as the information would be less relevant to the G_1 operator. The reverse is also shown in figure 10 and figure 11 for a G_2 operator, where the G_1 rule base is lowered and the G_2 rule base is raised. It can be seen that this simple rule change can have a large impact on the final scores output by the system.

Examples for possible data visualization designs for use in a dynamic user interface are shown in figure 12 and figure 13. The layouts show simple representations of high and low relevance of current information for the two grinders. Another design is shown in figure 14. The design implements a NLD layout. The scores are used to change to color and size of the grinder nodes. Large red nodes mean that the represented entity is of high

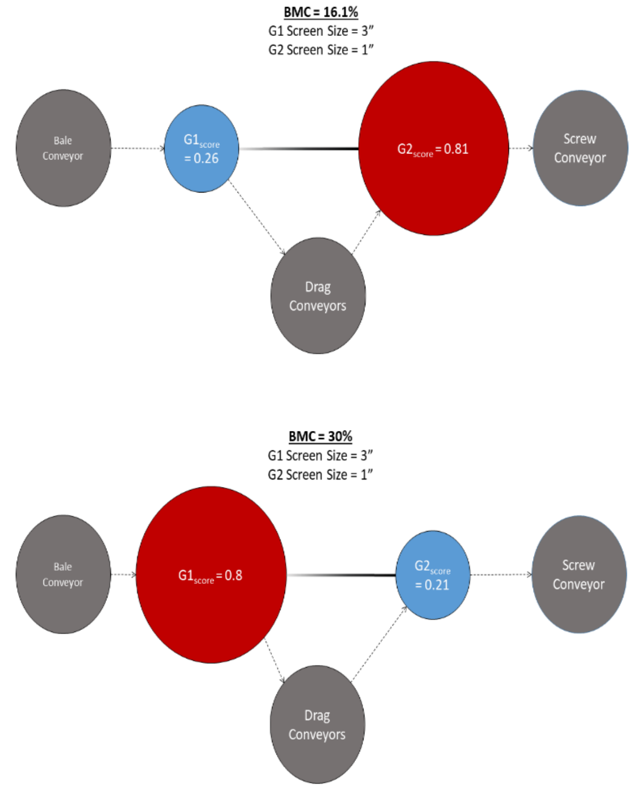

Fig 14: User Interface Examples with NLD Diagrams

relevance, while smaller blue nodes represent less relevant entities. The gradient bar between the G_1 and G_2 nodes indicates that the output of G_1 affects the functionality of G_2. Directional arrows are used to show the directional flow of the pipeline. Thus, the operator can quickly identify which components need close monitoring in that situation.

V. Conclusions

This paper presented a two-fold framework for enhancing situational awareness in control systems by dynamically optimizing visualizations. The first part of the framework defined information relevance by implementing a fuzzy logic inference system. The relevance was determined through a set fuzzy rules embedded into the system using predefined expert knowledge. The fuzzy scoring system was shown to successfully reflect the embedded expert knowledge to assign relevance scores to the available information. The second part of the framework involves applying the derived relevance scores to a visualization method to increase the system awareness of the user by removing visual clutter and emphasizing information that is more relevant to the user for decision making given the current state of the system. Several visualization methods that could take advantage of the proposed framework were discussed. As future work, a more robust fuzzy methodology for scoring will be implemented to further enhance the generality and usefulness of the system. The proposed scoring system will be applied to a visualization scheme with applications towards increasing situational awareness in control systems.

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