Eye Tracking Assisted Human Factor Analysis Platform for Power System Situational Awareness

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Abstract- **Data presentation techniques in power grid operations are important in determining situation awareness for control room engineers and operators. While innovative displays can be designed to convey static, dynamic, and other relevant attributes of grid information, an arising concern is their effectiveness in enabling control room operations. This paper presents an integrated architectural platform for performing human factors experimenting and analysis for power systems situation awareness. It leverages eye-tracking and other biosensing devices in simulated power system operations to capture critical human behavior data that can be further analyzed to extract qualitative and quantitative metrics in defining grid situation awareness. The architecture is designed to enable the assessment of presentation techniques and behavior of users (otherwise, known as respondents) either in real-time simulated grid operations, or offline when conveying the current state of the grid through static displays.**

Index Terms: Situation awareness, Human Factors, Power System, Visualization, Eye-tracking

I. Introduction

Techniques in power system information display, visualization, and analysis aim to communicate large amounts of multifaceted aspects of static and dynamic information as one holistic interpretation of the evolving health of the underlying grid. An accomplishment of this goal increases grid visibility while improving the situational awareness of engineers monitoring the power system [1, 2]. In the presence of innovative visualizations [3-9] however, it becomes imperative to assess these methods for their effectiveness in relaying information that adequately captures grid states. The creation of a true mental abstraction of the status of the grid will in turn enable engineers in their bid to adequately plan and control the power system. Several techniques are proposed to address situational awareness in the ever-growing and complex, interconnected power system networks. However, the burden to prove intuition and effectiveness becomes challenging when quantitative measures are not demonstrated. The inherent potential in systematically designed power system visualizations that would have otherwise be useful for improved situation awareness may thus become less exploited and under-utilized.

An actual human factors power systems experiment in [10] to assess acknowledgment speed of voltage violations in an IEEE 118-bus system showed a method of color contouring to provide the quickest response from respondents. The response time is a good metric in assessing the effectiveness of the presentation method. However, a true comprehension of complex, real-life grid scenarios will normally involve a more detailed behavior analysis reflecting the level of situational awareness prior to implementing control actions or proposing longer-term system planning activities. For example, recursive actions involving repeated eye pupil traversals and varying gaze levels across the screen for color depth comparisons and thresholds, and assessment of system capacity will need to be performed to build an abstract picture of the underlying system [11, 12].

The goal of this paper is in two folds. First, an eye-tracking assisted human behavior analysis platform is proposed following which experiment processes are discussed in a second step. Here, feasible metrics from the analysis of biosensing data for capturing and assessing systemic levels of respondent attention will be discussed. This paper proposes an eye tracking-based human behavior analysis platform for power system operation. By incorporating biosensing eye-tracking systems and multiple data sources, we investigate the potential to use physiological data to quantify the effectiveness of these visualization and analysis techniques. Furthermore, it aims to assess a respondent's situational awareness of the power system. The objective of this work is to develop a platform to obtain qualitative and quantitative metrics that measure the effectiveness of methods used for conveying power system operational and situational information to engineers.

II. Related Works

As an improvement to numerical displays used to present magnitude data at system bus locations, [3] proposed the method of contour visualization to show wide-area system voltages. It leveraged the contiguous space existing among buses that were spatially and geographically distributed within a power system. This technique emphasized the ability to observe wide-area information that instantly showed regions with voltage issues and trends in static snapshots (and aggregated, time-varying dynamics) that may otherwise not be immediately perceived if only numeric displays were used. A similar contour process was deployed in presenting frequency information in [13]. Furthermore, an expansion of this method to include geographically-displaced objects used for encoding phasor magnitude and angle data resulted in the use of geographic data view (GDV) objects to present global grid dynamics as wide-area oscillation mode shapes were visualized in a power system [5, 9]. In order to present multiple types of data fields for electric grid objects, regarding operational

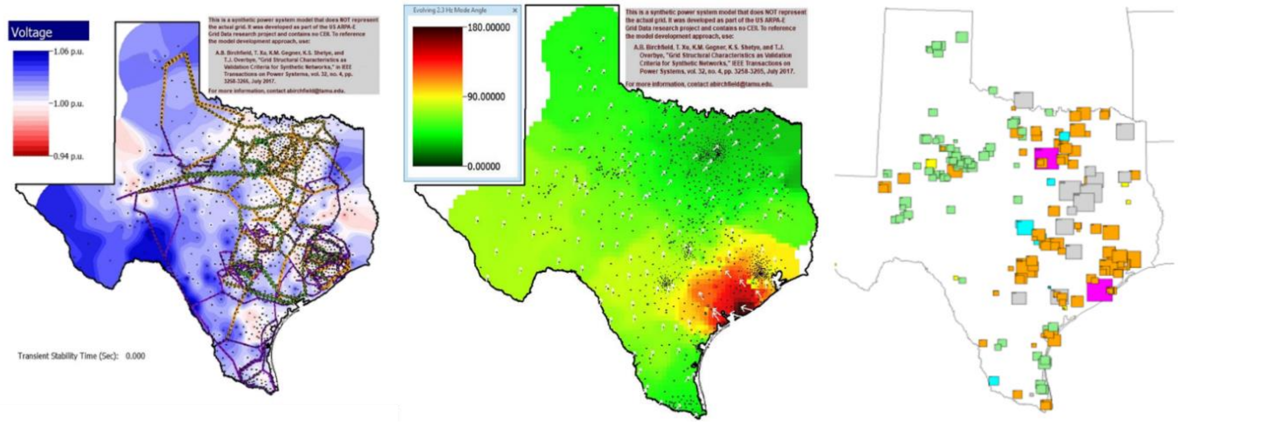


Fig. 1. (a) Colored voltage contour (b) 2.3 Hz mode shape GDV/contour (c) Generation capacity/type - 0% mosaic display

statuses (e.g. wide-area generator dispatch and available capacities, line/transformer limits and also bus voltages), mosaic and packing algorithms was proposed in [4, 6] to visualize large- scale electric data. The algorithms made it possible to generate and transition pseudo-geographic mosaic displays (PGMDs) into non-overlapping ones while efficiently using available display space.

Figure 1 shows applications of some of the mentioned techniques when wide-area visualizations are performed for different states in a synthetic 2000-bus system that is laid over the geographic boundaries of Texas [14-16]. In Fig. 1(a), the contour provides a voltage profile of the grid using pre-defined high (blue) and low (red) levels of the color spectrum to encode nodal per unit voltages. The contour in Fig. 1(b) shows the coastal region in anti-phase to the rest of the grid when a 2.3 Hz mode shape is observed in a forced generator oscillation. The extent of opposition, indicated by the GDV arrow object used to encode the relative magnitude of the mode shape, helps to reveal the generator oscillation source. Finally, Fig. 1(c) conveys status of all generators in the grid by leveraging color and relative size properties of GDV objects to convey information about the fuel type and capacity, respectively. The large pink nuclear units and eastern green wind units can be instantly observed. Implementation of packing algorithms in Fig. 2 spreads out the GDVs in pseudo-geographic, non-overlapping mosaic styles to further improve the situation awareness of the electric grid control room personnel.

Power system visualization techniques are driven by their intended ability to improve the grid situation awareness of power systems engineers by presenting large amounts of power system data in a quick and concise manner. In turn, this would aid faster and more effective control actions and decisions. As innovative techniques evolve, however, the qualification of the effectiveness of these methods prompts empirical/experimental methods aimed at understanding user action models and the effectiveness of designed visualizations.

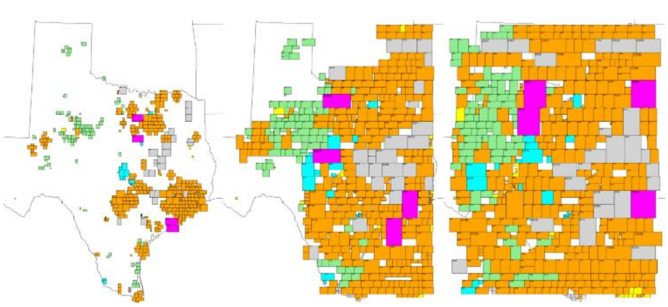


Fig. 2. Generator pseudo-geographic mosaic scaled to 10%, 50%, and 80% of the display space, respectively. Relative size and coloring representation generation capacity and fuel type

A method to develop a task diagram (sequence of performing tasks) for an unplanned switching event in a control room was implemented in [17]. Through the application of cognitive task analysis and decision making via operator cues and personnel interviews, the study constructed abstract models and sequences of tasks performed by the subject. In real scenarios, control room personnel are inundated with lots of grid information obtained from different sources. Simultaneous tracking of external environmental stimulus, alternative courses of actions, and the justification of selected actions may prove to be a burden for personnel needing to respond to assessment questions designed to uncover mental tasks and sequences. By complementing the cognitive task analysis with biosensors that bear little or no impact on a subject's performance and course of action, subtle and qualitative behaviors obtained from the personnel may provide better input data to construct more effective task diagrams.

In [18], comparative analysis between experimental groups was used to assess the usefulness of visualization tools in situation awareness followed by post-experiment interviews to examine the decision-making models utilized by personnel and operators of an electrical grid. Here, the data gathering process included the use of audio and video for each subject, screen video capture, video capture to capture actions and thoughts in a talk 'talk-aloud' process and finally post-scenario interviews. In goal-directed tasks that utilize visualizations, simply talking aloud and screen capture may not fully guarantee a correlation with a subject's visual search behavior which is known to contain more rich information on user attention and control [19]. However, by correlating multiple areas of interest (AOIs), eye gazes and fixations of subjects with their immediate actions, the inclusion of an eye data capture tool would generate qualitative input information for better examining the operator decision model. More importantly, it also has the potential to inform on the effectiveness of visualizations by assessing gaze patterns, AOIs and other subtle cues that the subject may have ignored and failed to report in the interview stage. Furthermore, the method of tracking subject visual search independently may overcome over-reliance on comparison studies in cases where performance levels may need to satisfy defined standard metrics. For example, the time needed for a subject to first visually observe an evolving grid disturbance on the interface, and time taken to respond may be metrics of interest.

III. ARCHITECTURE

With the goal to provide objective and quantitative results for human-involved experiments regarding power system application, this integrated platform is developed with multiple biometric sensors and interactive-oriented programs. Eye tracker, environment camera, screen and event recorder together form the basis of measurements. Programs are developed respectively for the types of online and offline studies. For the online study, Dynamics Studio (DS) [20] and W4IPS [21] are used to provide interactive dynamic grid environments for users to operate. Additional data, like system measurements, are collected during the interactive simulation along with those biometric data. These data are then synchronized, processed, and analyzed in iMotions [22], a software for analyzing data obtained from eye tracking sensors and other external sources. Application Programming Interface (API) also exists to be used with Python for extending analysis capability and flexibility. For the offline study, which is normally used with offline media, like static images and video, a program is developed to host those media and provide a uniform interface to receive users' direct feedback. This type of study is especially useful when a new visualization technique is developed and wants to be compared with other existing techniques.

Figures 3 and 4 show the architecture of the proposed platform, and its online usage to quantify the user's awareness while operating a simulated power grid, respectively. In Fig. 3, the architecture for the proposed behavior analysis platform is designed on top of an interactive power system dynamic simulation (IDS) environment and an offline media hosting environment. System events, measurements and online assessment metrics are transmitted to the integrated analysis platform, where they are merged with physiological data from biosensors (e.g., gaze movement, mouse movement, keyboard events, etc.).

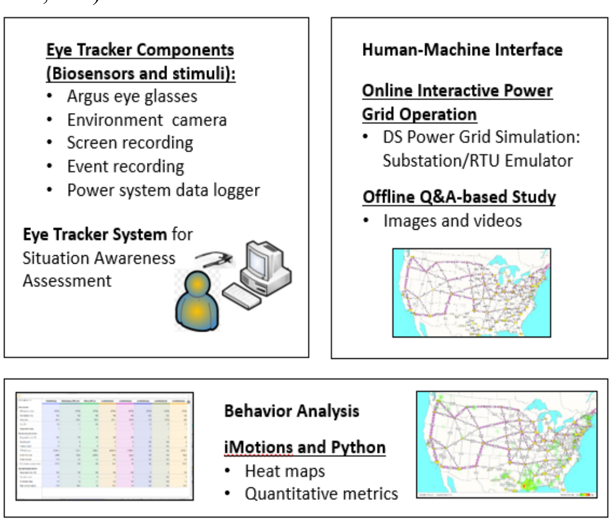


Fig. 3. Architecture for the proposed behavior analysis

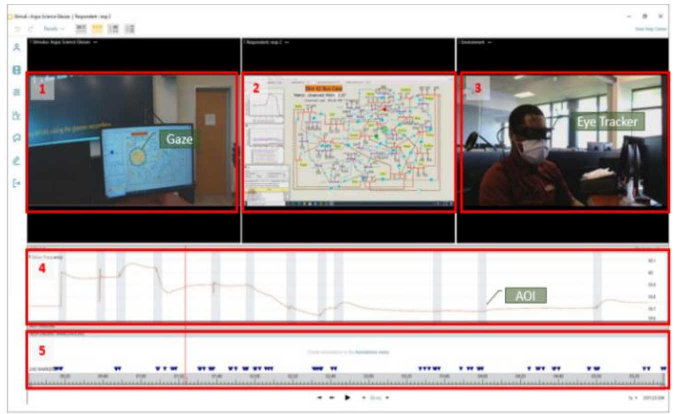


Fig. 4. Interface for an integrated analysis platform

The interface for the integrated analysis platform, shown in Fig. 4, demonstrates the use of multiple biosensors and data sources. By incorporating data from the eye tracker (segment 1), environment camera (segment 3), grid measurements (segment 4) and user events (segment 5), area of interest (AOI) can be quickly identified and metrics indicating awareness level can be calculated during the operation of a power system (segment 2).

Using the online study as an example to illustrate how the platform works. As can be seen in Figure 4, during the simulation the system frequency is not always stable. This is largely due to the pre-set contingencies in the case and the user's operation. To investigate how the user operates, as a pre-process we first label the moment/period when system frequency has a dramatic change as AOI (temporal) and perform a gaze mapping so that irrelevant eye gaze movement outside the interested area will be ignored. Then different gaze analysis could be done on the aggregation of AOIs:

1) Gaze path: gaze path shows the location, order and time spent looking at locations on the stimulus. It could be used to analyze the operator's looking pattern and risk awareness, especially under the pressure when contingency happens.
2) Heat map: heat map shows how gaze is distributed over the stimulus during the AOI. This duration-based heap map could help indicate whether the operator knows where to check and where the system vulnerabilities are when contingency happens.
3) Dwell time: the total amount time spent when gaze is within AOI (spatial). This metric function is similar to heat map but provides a qualitative value for evaluating the operator's situational awareness.
4) Time To First Fixation (TTFF): the time to first fixation indicates how long does it take for a respondent to take notice or fixate upon an AOI segment affected by a stimulus introduced into the experiment. In relation to power system operation, whether an operator can determine where the contingency is likely to be located and how to solve it in shortest time could be partially quantified/verified/validated by this metric.

These four analyses are only an example to help understand how the platform work after collecting the data. They do not represent the full analysis capacity of the platform.

IV. USE CASES

The goal of this section is to explain the procedures that is developed for the experiment and post analysis. By taking advantage of the inter-correlation of human behavior and specific tasks on a human machine interface (HMI), the measurement and analysis processes are carefully designed and conducted to provide meaningful quantitative results. Two studies are included here to demonstrate the procedure and the capability of the integrated platform.

A. Experiment and Analysis Flow

As shown in Fig. 5, multiple real-time data streams are captured during the experiment, regardless of whether it is IDS-based or offline-media-based. Once data collection from the experiment is completed, a pre-analysis process involving data synchronization will be used to generate a uniform-length multi-channel dataset for each respondent.

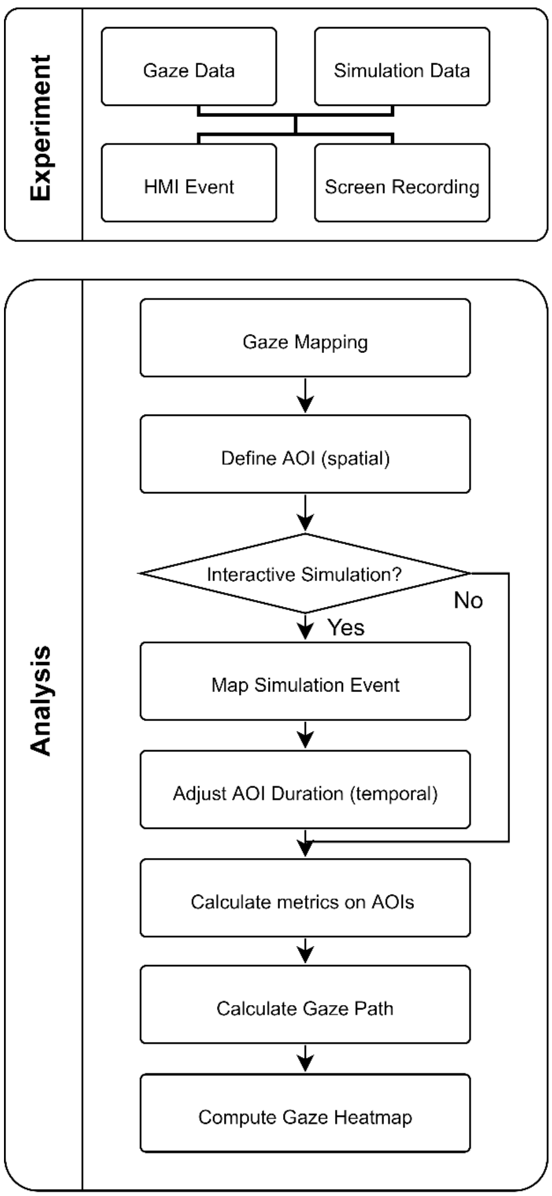


Fig. 5. Flow chart of the procedure developed to be used with the platform

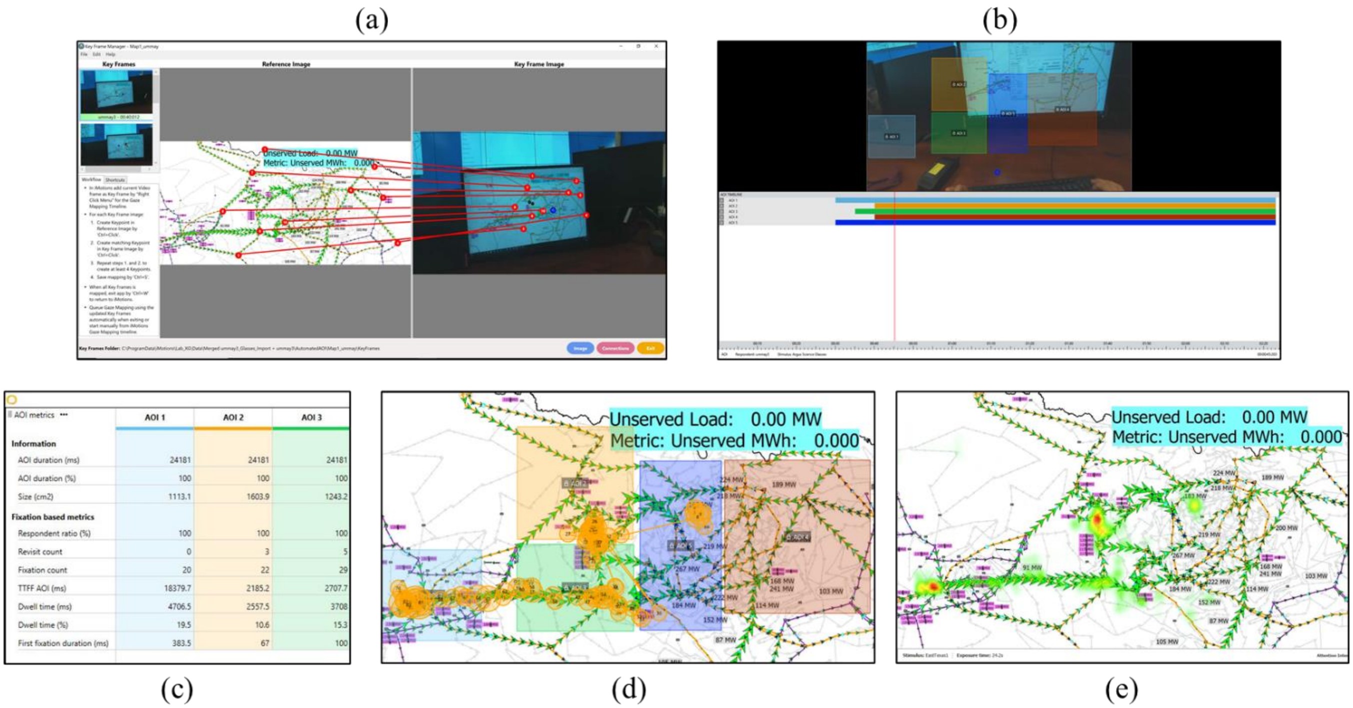
This dataset, processed by data synchronization, however, cannot be directly used for AOI analysis since external mobile eye tracking glasses are used in the testbed. Unlike screen-based eye tracking system which provides gaze data using native screen coordinates as reference, the eye tracking glasses uses respondent's view as coordinate system and provides gaze data with its reference. Thus, a gaze mapping process [22] is necessary to project the generated gaze data to the required visualization media which for the studies carried out in this paper is the computer monitor. The benefit of this type of eye tracker is its capability to be used with various visualization media (e.g., main screen of utility control centers [23]). The gaze mapping is a process of transforming a 3-D visual scene (respondent's view) into a 2-D perspective (screen recording) as demonstrated in Fig. 6a. Here, multiple point-to-point mappings are established between a reference frame (located on the left) and a chosen frame from the eye glass data (located on the right) to help the software establish the correlation between the 3-D and 2-D scenes. A machine learning technique then performs gaze mapping to translate positions of the eye-tracker cursor of the respondent's 3-D scene onto the 2-D reference image on the computer monitor.

Further, AOIs are defined on the referenced frame. As shown in Fig. 6b, a single study is shown to have multiple AOIs originally defined on the reference frame. In the figure, it is observed that different sizes and orientations have been specified. Since their shape, location, and duration have significant impacts on computed metrics, AOIs should be carefully determined and specified for each task. In the IDS-based study, additional temporal AOI durations may be specified according to individual simulation events. This is enabled by embedded tags included in the simulation timeline.

Finally, statistical information generated for each AOI is obtained after an analysis is performed on the software platform. In Fig. 6c, duration and fixation-based metrics (TTFF, dwell time) for each AOI is shown. These results provide statistical metrics that evaluate respondent's attentiveness, responsiveness, and their perception over each AOI. Also, summary visualizations of eye movement on the HMI for the entire simulation duration can also be extracted. For example, eye gaze path and gaze heatmap in Figs. 6d and 6e, respectively, can be analyzed to provide additional insight about the respondent's behavior when responding to tasks during the simulation. This evaluation helps to quantify the effectiveness of the target visualization technique.

B. Study 1: Interactive Simulation-Based Study

In this study, the respondent's task is to prevent the collapse of an electric grid in a tornado scenario. The interactive dynamic simulation case is developed on top of a synthetic Texas power grid [14-16] and IDS, and the respondent is permitted to adjust generation dispatch, switch shunts and shed loads, when necessary, to prevent system-wide blackout while minimizing the total unserved loads. In the simulation, a "tornado" causes multiple line and generator outages in the mid Texas area at different time instances. Two respondents (A:



AOI metrics	AOI 1	AOI 2	AOI 3
Information			
AOI duration (ms)	24181	24181	24181
AOI duration (%)	100	100	100
Size (cm2)	1113.1	1603.9	1243.2
Fixation based metrics			
Respondent ratio (%)	100	100	100
Revisit count	0	3	5
Fixation count	20	22	29
TTFF AOI (ms)	18379.7	2185.2	2707.7
Dwell time (ms)	4706.5	2557.5	3708
Dwell time (%)	19.5	10.6	15.3
First fixation duration (ms)	383.5	67	100

Fig. 6. (a) Map the gaze data from eye-tracking view to screen recording (b) Define the AOI and adjust the AOI timeline based on simulation event (c) Calculate metrics (Dwell time, TTFF, etc.) for each AOI (d) Analyze the gaze path during the experiment (e) Compute the gaze heatmap

post-doc and B: first-year graduate student) with different experience levels of the simulation case assume the task of managing grid operation in the platform after which their performances were analyzed and compared.

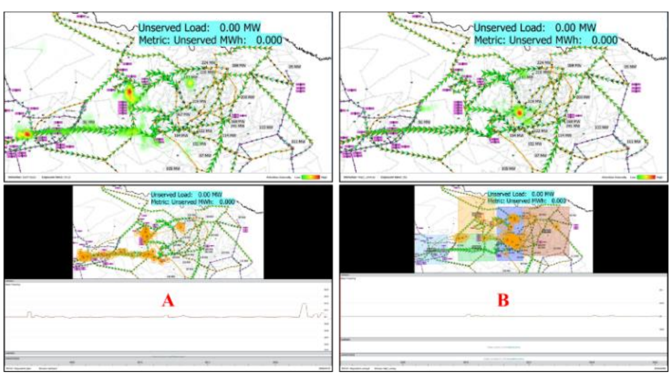


Fig. 7. Comparison of gaze heatmap and gaze contour between two respondents in IDS study

As shown in Fig. 7, the heatmaps and gaze paths indicate a significant behavior difference between the two respondents. Respondent A constantly monitors a major mid-west 500-kV transmission line and its nearby area once the "tornado" causes an outage of a neighboring 500-kV transmission line. Respondent A monitors this mid-west line by re-dispatching nearby generation to prevent line overload while simultaneously ensuring sufficient power supply in the mid-west area. In comparison, however, it was observed that respondent B spent most of the time staring at the mid area (as observed by the sole 'hotspot' area in the heatmap). Possible

A

AOI metrics	AOI 1	AOI 2	AOI 3	AOI 4	AOI 5
Information					
AOI duration (ms)	24181	24181	24181	24181	24181
AOI duration (%)	100	100	100	100	100
Size (cm2)	1113.1	1603.9	1243.2	2737	1688.6
Fixation based metrics					
Respondent ratio (%)	100	100	100	0	100
Revisit count	0	3	5	NA	2
Fixation count	20	22	29	NA	9
TTFF AOI (ms)	18379.7	2185.2	2707.7	NA	168.7
Dwell time (ms)	4706.5	2557.5	3708	NA	1267.5
Dwell time (%)	19.5	10.6	15.3	NA	5.2
First fixation duration (ms)	383.5	67	100	NA	83.5

B

AOI metrics	AOI 1	AOI 2	AOI 3	AOI 4	AOI 5
Information					
AOI duration (ms)	25995	25995	25995	25995	25995
AOI duration (%)	100	100	100	100	100
Size (cm2)	1113.1	1603.9	1243.2	2737	1688.6
Fixation based metrics					
Respondent ratio (%)	0	100	100	100	100
Revisit count	NA	0	2	2	5
Fixation count	NA	1	7	4	65
TTFF AOI (ms)	NA	12.7	7751.7	4523.7	735.2
Dwell time (ms)	NA	244.5	2322	605.5	18018
Dwell time (%)	NA	0.9	8.9	2.3	69.3
First fixation duration (ms)	NA	244.5	166.5	205.5	88.5

Fig. 8. Comparison of AOI metrics between two respondents

reason was the minimal comprehension that respondent B possessed prior to working on the tornado simulation case.

The above observation could also be supported by the metrics obtained from the AOI analysis. Fig. 8 shows metrics obtained for the two respondents. Each column shares the same color as the corresponding AOI block shown in Fig. 6d. From the dwell time ratio, it is obvious that respondent A distributes attention relatively equally across four AOI zones (ignoring AOI 4 area located far away from the tornado disturbance), while respondent B spends most of time (69.3%) on the mid area (AOI 5) still trying to comprehend the case. Fixation count shows a similar pattern for respondent B: 65 out of 77 of fixations are in AOI 5.

C. Study 2: Offline Material-Based Study

In addition to an IDS-based study, the platform can also be used in an offline setting such that input materials (static images, GIFs, videos, and website) can be uploaded in the software that is developed for an experimental study. Tasks and questions can then be included while presenting the materials to the respondents. Currently, the setup has been configured to support two types of questions: forced selection and search-and-click. Then, computer mouse movements and click events are collected and labeled as tags in a merged dataset recorded by the software platform.

Fig. 9 shows result images of merged AOIs and a heatmap when two different respondents (A and B) were told to separately watch a 24-s, animated color contour which summarized fictitious 24-hr locational marginal price (LMP) variation in a grid simulation of a 7K-bus system. Here, the respondents did not have to respond to any specific tasks/questions in the experiment study. However, significant differences and similarities observed from both images provided insights on the behavior of both respondents when watching the animation. For example, respondent B (less familiar with the LMP animation than A) spent relatively more time trying to understand the animation as shown by the higher intensity of heat spot in the areas surrounding the fuel-type legend and contour color key. However, both respondents were able to significantly identify the boundary experiencing significant price differences within the system as observed by the amount of time spent in AOI 4 (covering the east and part of north-central regions). In this area, a heavily congested transmission line was observed to cause wide LMP variations between both connecting bus ends of the line.

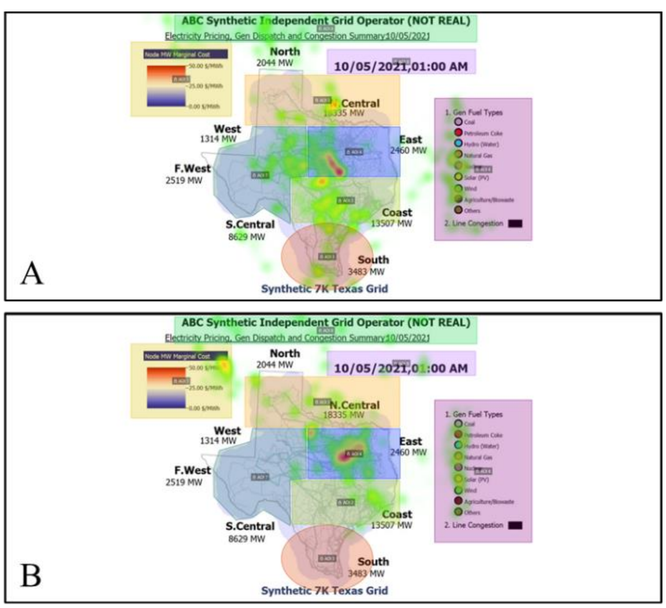


Fig. 9. Comparison of heatmap between two respondents in offline mode

V. Conclusion

The need for quantifying situational awareness in control rooms and the effectiveness of visualization methods has been a long-term challenge, especially as grid visibility and newer methods of presenting power system information are evolving. Addressing this type of human factors perceived questions not only requires power system expertise, but it also requires a comprehensive and quantitative framework to conduct experimental studies, analyze biodata and evaluate results. In this paper, we present an integrated eye tracking based human factor analysis platform for power system situational awareness and visualization evaluation. The platform is introduced from architecture, usage procedure and prospective use cases. Two example studies, comprising interactive simulation-based and offline material-based studies, are presented to demonstrate the capability of the developed platform to provide meaningful qualitative and quantitative metrics that can be further analyzed to generate meaningful insights for situational awareness. The platform will be used to help develop better visualization methods for power system applications.

VI. Acknowledgement

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