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Buah Eric, Linnanen Lassi, Wu Huapeng

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Emotional responses to energy projects: a new method for modeling and prediction beyond self-reported emotion measure

Buah, Eric^{a*}, Linnanen, Lassi, ^b Wu Huapeng^c

^{a,*,c} School of Energy Systems, LUT University, Lappeenranta FI-53851, Finland

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ABSTRACT

A considerable amount of studies report that negative emotions evoked by Wind Energy, Nuclear Energy and CO₂ Capture and Storage (CCS) can lead to cancellation of the energy project or a delay in policy decisions for its implementation if not adequately addressed. Earlier studies have attempted to study this problem using self-reported emotion measurements to identify the emotions the participants felt. As an alternative, we propose the use of an emotional artificial intelligence (AI) algorithm for improved modelling and prediction of the participants' emotional behaviour to guide decision-making. We have validated the system using emotional responses to a hypothetical CCS project as a case study. Running our simulation on the experimental dataset (thus 40% of the 72,105), we obtained an average validation accuracy of 98.81%. We challenged the algorithm further with 84 test samples (unseen cases), and it predicted 75 feelings correctly when the stakeholders took a definite position on how they felt. Although there are few limitations to this study, we did find, in a sensitivity experiment, that it was challenging for the algorithm to predict indecisive feelings. The method is adaptable to study emotional responses to other projects, including Wind Energy, Nuclear Energy and Hydrogen Technology. © 2019 xxxxxxxx.

1. Introduction

The study of emotional responses to controversial energy projects is a growing area of interest in technology acceptance literature. Earlier studies reported that the negative emotions evoked by these technologies could lead to the cancellation of energy projects or a delay in policy decisions if the communities' emotional responses and the resulting behaviours were not adequately addressed (Roeser et al., 2012; Roeser & Pesch, 2015; Huijts, 2018; Janhunen, 2018; Perlaviciute et al., 2018). This phenomenon suggests that if the project developers had the capability to predict sentiments and emotions early in the development of the project, that interventions could be introduced to manage the community's emotions and behaviours, hopefully increase the likelihood of the project's acceptance. In recent literature, Perlaviciute et al. (2018) wrote, "while practitioners are increasingly realizing that they cannot simply ignore public emotions, they

struggle with how to deal with people's emotional responses and how to secure public acceptability of sustainable energy projects" (p.1). Lazarus (1991) and Barrett (2017) studies increased our understanding that emotions can be addressed because they are self-constructed by the stakeholders from their cognitive appraisal of the project and its facilities. The cognitive appraisal is an immediate, unconscious appraisal and it mediates the stimulus events that evoked the emotion and the corresponding responses. In the cognitive appraisal process, the emotions are created using what Barrett (2017) preferred to call "cognitive ingredients." Lazarus (1991); Breiman, (2001); Shmueli (2010) and Barrett(2017) reported that if the linear and non-linear relationships between the thought process and the outcome behaviours could be explored and understood, then a protocol could be developed to predict future behaviours, allowing the project managers to design appropriate interventions.

* Corresponding author. Tel.: +358 44 2929862

E-mail address: eric.buah@gmail.com

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Earlier studies have attempted to measure and model the relationship between emotions and behaviours using various social science methods. The most frequently used method in the technology acceptance literature has been a self-reported emotion measurement combined with other conventional statistical techniques. Investigators relied on respondents to accurately and honestly report their affective emotional responses to the energy project (Ciuk & Troy, 2015). It was implemented using positive and negative affective words such as satisfaction, pride, joy, hope, calmness, worries, annoyance, aversion, stress, powerlessness, and fear that were relevant in the context of the technology in question. Depending on the researchers' objective, the measure could either be valence focused or arousal focused. In this way, the intensity of the subjective emotional experience could be captured by asking the respondents to report how much they felt the emotion reported on a psychometric scale, such as a Likert scale (Feldman, 1995; Midden & Midden, 2009; Bruine de Bruin, 2014; Perlaviciute et al., 2018; Huijts, 2018).

Wilson and Gilbert (2003) wrote that the strength of this method was in its "proven track record of reliability and validity." Its strength was that the subjective emotional experience was self-reported by the subjects who felt the emotions themselves in relation to the energy projects. It was not an investigator or machine attempting to guess the participants' emotional responses. It was reliable and accurate, especially if social desirability bias was minimized and well managed in the data collection process.

Social desirability is a limitation that occurred when people expressed their thoughts and feelings in a way they deem to be more socially acceptable, even if it was not their more accurate or "true" thoughts and feelings. This phenomenon caused those on the high social desirability scale to be dishonest about their own feelings or hesitant to give completely honest answers if such answers were perceived to be socially undesirable (Paulhus & Reid, 1991; Welte & Russell, 1993). The desire to answer with a socially acceptable response was more likely to occur in the direct engagement process where focus group or face to face interviews occurred with the respondents seated near the interviewers.

Another limitation of this method was that people had a difficult time pinpointing specific reasons for their attitudes which made it challenging to understand the respondents' thoughts and the actions (Ciuk & Troy, 2015). This inability limited the decision-makers' efforts to develop the capability to predict future emotions and behaviours to create targeted interventions. Some studies had attempted to ask respondents to report their future cognition, including their emotions, using different information to enable the researchers to observe how behaviours changed. They hoped that the participants could predict their own behaviours based on their anticipated future emotions.

Wilson & Gilbert (2003) found that humans are good at predicting their present emotions, but less accurate at predicting their future emotional responses, even if it involved a previously experienced emotional trigger. One of the reasons was that the human emotional experience is highly influenced by time. People were unable to accurately predict future emotions and sentiments due to a knowledge deficit of how future events might impact their feelings. This limitation suggested that the self-reported measurements used in collecting post-test behaviour was not robust enough to help researchers accurately predict future emotions and behaviours. An alternative method of data collection was necessary. This study attempts to

overcome these limitations and contribute to the existing technology acceptance literature.

This study's goal is to overcome limitations by proposing an emotional artificial intelligence (AI) algorithm for improved modelling and prediction of the participants' emotional behaviour to guide policy and company' decision-making. It uses fuzzy deep learning techniques. It uses this technique because of the pioneering work on human reasoning by Zadeh (1965;1975) that stated that human reasoning and behaviours are imprecise, ambiguous, vague and fuzzy. Fuzzy deep learning tradition fosters cooperation between fuzzy logic and deep neural network to observe a behaviour that is fuzzy, imprecise and vague and takes into consideration the uncertainties in the data. This combination result in hybrid deep learning models that are not only more accurate but better at interpreting the influence of the environment on the behaviour it observed. ((Bonanno et al., 2017; Deng et al., 2017). Our study is based on these these ,machine learning theories.

Our paper is limited to a case study of the practical feasibility of identifying the emotional responses to a hypothetical CO₂ storage of a CCS project. CCS technology involves three major steps; capturing CO₂ at the source, compressing it for transportation, and then injecting it deep into a rock formation at a carefully selected and safe site, where it is permanently stored. CCS is an interesting case because it is controversial; however, it has gained attention among practitioners and researchers in international climate legislation discourse such as the Paris Agreement which became effective on 4 November 2016. CCS will enable continuous use of fossil fuel but on the other hand, when combined with bioenergy, negative emissions are created. Expert proponents, such as Global CCS Institutes, claimed that under stringent emission scenarios that it is seen as a method for meeting the 1.5 degrees Celsius ambitious target in the Paris agreement. On the other hand, opponent experts, such as Greenpeace, see CCS as an environmental scam where industries are trying to buy time to enable continued fossil fuel use instead of exploring new and more radical energy approaches.

Citizens who will be faced with having CCS energy projects in their local communities are influential stakeholders in the decision-making process (IEA, 2010). In some countries, such as the Netherlands and Germany, the storage facilities have triggered emotions and sentiments that brought demonstrations that caused CCS plants to a stop operations (Ashworth et al, 2011). Huijts et. al (2012) found people's responses to CCS and the cognitive elements they used to make those responses are like those of Hydrogen technology, Wind Energy, and others controversial energy technologies, including Nuclear Energy projects. Our proposed study's adaptability to other energy technologies makes it interesting and relevant. We propose that using our AI algorithm will make it easier for our colleagues to observe our step-by-step process and adapt this method to their own studies, replicating our findings with other alternative energy technologies.

Our paper is divided into 4 sections. This section introduced the problem and our proposed solution. In Section 2, the AI model is presented with a brief explanation of its working principles and mathematical logic. In Section 3, a simulation experiment demonstrating the capability of the system is presented. In Section 4, a discussion of the results and a concluding remark is presented.

Nomenclature

X^{FL} Fuzzy Likert representations (Likert responses incorporate with fuzziness so that it degree among other thoughts can be measured and well represented on the psychometric scale without limitation).
 $\mu(x)$ Degree of membership (membership function)
 MF Membership function. The same as degree of membership
 CCS Carbon dioxide capture and storage
 DNN Deep neural network
 Hybrid Fuzzy-DNN Combination of fuzzy logic and deep neural network
 X_{trust} Psychological response of trust in actors
 x_{Risk} Psychological response of a subject's risk perception on the energy project measured on a Fuzzy Likert scale
 Y Crisp value of the emotional state fired by the algorithm after multiplying weight factor by a psychological response of a subject to determine its affective state, whether pleasant or unpleasant or indecisive feelings.
 X A subjective response to a stimuli (raw response)
 PA Expression of pleasant feelings
 NA Expression of unpleasant feelings
 MOD Expression of Indecisive feelings
 $\mu_{i\ don't\ know}(x)$ Membership function of indecisive feelings of a subject.
 $\mu_{sad}(x)$ Membership function of a subject unpleasant feelings (low dearth negative emotional response such as sad,).
 $\mu_{worried}(x)$ Membership function of a subject unpleasant feelings (high dearth negative emotional response such as Worried, I am afraid etc.).
 $\mu_{happy}(x)$ Membership function of a subject pleasant feelings (high dearth positive emotional response such as excited, I am very happy etc.).
 $\mu_{calm}(x)$ Membership function of a subject pleasant feelings (low dearth positive emotional response such as calm).
 TSK Takagi–Sugeno–Kang (TSK) fuzzy system
 TSK meta algorithm responsible for reasoning and combining decisions of fuzzy inspired DNN algorithms using Takagi–Sugeno–Kang (TSK) fuzzy if-then rules

2. Materials and Method

2.1. Architecture of the proposed algorithm: CCS as a case

Fig. 1 represents the architecture of the proposed artificial emotional intelligence algorithm for modeling and predicting emotional responses to energy projects using CO₂ Storage technology as a case. Theoretically, the proposed algorithm establishes its human-level knowledge from psychological and technology acceptance theories. It is based on the theory of constructed emotions (Barrett (2007; Barrett, 2017), Lazarus cognitive-appraisal theory (Lazarus, 1991) dimensional theory of emotion based on the circumplex model (Russell, 1980; Posner, Russell & Peterson, 2005) and Huijts et al (2012) technology acceptance framework. Building conceptual bridges between these psychological theories, the algorithm is built on the theoretical assumption that the emotions and sentiments (outcome behaviours) evoked by the energy projects and its facilities (stimulus event) are self-made by the citizens and their network of stakeholders. In constructing the emotion, when the people encounter the energy project (such as CO₂ Storage), the concerns that are raised by the people and how they cognitively appraised those concerns are what they use as predictors in their brain to make their emotions and form an overall

perception towards the system. This cognitive appraisal is an immediate, unconscious appraisal and it mediates between the stimulus event and the emotional responses (for more review refer to Lazarus, 1991; Barrett, 2017). In the work of Huijts et al (2012) many of these predictors that play a role in the thought process of people when appraising sustainable energy projects are highlighted. Our algorithm learns and models the non-linear dependencies in this reasoning to predict emotional behaviours from the cognitive thinking process of the people using a hybrid fuzzy deep neural network (Fuzzy-DNN) algorithm.

Our Fuzzy-DNN algorithm is a hybridization of fuzzy logic and deep neural network algorithm. In this architecture, the fuzzy logic brings its human-like thinking into the decision process and the neural networks bring its biologically learning capability to capture complex patterns in the stakeholders' thinking process when appraising the energy projects.

As illustrated in Fig. 1, using this hybrid Fuzzy-DNN, the system carries out this cognitive reasoning task using three subsystems (Fuzzy Likert-TSK+DNN+TSK). It is a combination of Fuzzy Likert Inference system based on First-Order Takagi–Sugeno–Kang (TSK) fuzzy system, an ensemble of deep neural networks (DNN) algorithms with fuzzy-based rules and a first-order TSK meta classifier. During the emotional reasoning, each subsystem plays a different role. How the three subsystems are computationally connected to guess emotionally driven behaviour on CO₂ Storage in the CCS value chain or the behavior been observed by the researcher is inspired by the principles of stack generalization (Wolpert, 1992). Stacked generalization is an ensemble method that combines prediction of different learning algorithms into one using a meta algorithm (Wolpert, 1992; Naimi & Balzer, 2018). In the next section, we will present the working principles of the system and how each subsystem plays a role in the behavioural mapping to arrive at the outcome.

2.2 How the system acquires data and preprocesses the data

As indicated in Fig. 1, the system takes X as input where X is the appraisal of the CCS project or the energy project and its facilities in question via psychological predictors. The advantage of the system is that it can accommodate many inputs and therefore the number of predictors depends on the project researchers' own decision based on the problem at hand. In this data acquisition, X is measured on a Fuzzy Likert scale (see discussion for more details and also the work of Symeonaki & Kazani, 2011; Li, 2013). As shown in Fig. 1, when the algorithm receives the input X , it reconstructs this information into the Fuzzy Likert representations, X^{FL} using the TSK Fuzzy Likert Inference System (TSK FLIS). The TSK FLIS in our model is a rule-based system. It uses human experts' linguistic rules to perform this X to X^{FL} transformation. In fuzzy logic, a linguistic fuzzy rule R_s is represented as in equation 1:

$$R_s : \text{If } X_1 \text{ is } A_1^s \text{ and } \dots X_n \text{ is } A_n^s \text{ then } Y \text{ is } A_y \quad (1)$$

In reference to equation 1, in TSK-type fuzzy system, the consequent of the rule is a polynomial function of the input variables $P_s(X_1, \dots, X_n)$. The order of the TSK fuzzy system is determined by the degree of the polynomials used in their consequents, which can be either linear or constant. Since our algorithms use the first order (linear) TSK systems, the rule is expressed as in equation 2:

Fig. 1 Architecture of the proposed algorithm for modeling human data on CCS to predict how a stakeholder will emotionally receive the CO₂ Storage. It takes the User 1 information as X , pre-processed to X^{FL} using a low-level decision-maker (TSK Fuzzy Likert system). It then handover the low-level decision to a group of AI experts (ensemble DNN algorithms) for a higher level decision. After the DNN algorithms make the decision, a consensus is found using the TSK meta classifier using fuzzy reasoning, and inform human decision-makers on how User 1 feels about the proposed or the energy project underway.

$$R_s : \text{If } X_1 \text{ is } A_1^s \text{ and } \dots X_n \text{ is } A_n^s \text{ then} \\ Y = a_{s1} X_1 + \dots + a_{sn} X_n + b_s \quad (2)$$

From equation 2, given a set of rule base denoted as $\mathcal{RB}$, TSK inference system obtains the output as the weighted average (by matching degree) of the individual outputs generated by each rule

$R_s \in \mathcal{RB}$. Thus, given an input instance $e_1 = (x_1^l, \dots, x_n^l, y^l)$, the output is expressed as:

$$y^l = \frac{\sum_{R_s \in \mathcal{RB}} h_s^l P_s(x_1^l, \dots, x_n^l)}{\sum_{R_s \in \mathcal{RB}} h_s^l} = \frac{\sum_{R_s \in \mathcal{RB}} h_s^l v_s^l}{\sum_{R_s \in \mathcal{RB}} h_s^l} \quad (3)$$

where $h_s^l = T(\mu A_1^s(x_1^l), \dots, \mu A_n^s(x_n^l))$ is the the compatibility degree of the instance e_1 with the rule R_s ; T is a T-Norm; and $v_s^l = P_s(x_1^l, \dots, x_n^l) = a_{s1}x_1^l + \dots + a_{sn}x_n^l + b_s$ is the value of the polynomial in the consequent of R_s if the indeterminates take their values from e_1 (Cozar et al., 2017).

Using this first order TSK rule base system in Fig. 1, the Fuzzy Likert Inference engine uses five linguistic rules $R_s = (R_1 \dots R_5)$ to converts the X - variables to X^{FL} . The rules are;

R_1 If a Likert response is VERY LOW = 1, then, its corresponding Fuzzy Likert is VERY LOW $\rightarrow [0]$

R_2 If a Likert response is VERY HIGH = 5, then its corresponding Fuzzy Likert is VERY HIGH $\rightarrow [1]$

R_3 If a Likert response is MEDIUM = 3, then, its corresponding fuzzy Likert is MEDIUM $\rightarrow [0.5]$

R_4 If a Likert Response is LOW = 2, then, its corresponding fuzzy liker is LOW $\rightarrow [0.25]$

R_5 If a Likert response is HIGH = 4, then, its corresponding Fuzzy Likert is HIGH $\rightarrow [0.75]$

Fig. 2 An example of an explanatory model to study and capture relationship between predictors to explain and predict inclination to accept energy projects including CCS project (Huijts et al., 2012)

The X variables to X^{FL} transformation also comes with benefits that partly contributes in solving the small data problem in traditional deep neural network. First, since the interval details between the ordinal points on the Fuzzy Likert scale is known, it provides a high dimensional behavioural space on the Fuzzy Likert Scale to accommodate future values that are not represented on the scale. Secondly, this high dimensional behavioural space also allows data augmentation to be performed to extract datasets to augment original small training dataset to train a deep neural network. Evidence of this is demonstrated experimentally in section 3. This leads to the question of what will happen after the Fuzzy Likert Inference System has converted X variables to X^{FL} . This leads us to the next section on the theme, inferencing and high-level decision making using the ensemble fuzzy inspired deep neural networks.

The inferencing in our system is where the higher level decision-making takes place using an ensemble fuzzy inspired DNN algorithms. The algorithms are trained using the X^{FL} representations. Hence, it takes an unknown X^{FL} as an input and makes a guess of the likely emotional feelings using the inference engine of the ensemble fuzzy inspired DNN algorithms. Let's use *trust in actors* (X_{trust}) and *risk perception* (X_{Risk}) on the CCS facilities as case example. As illustrated in Fig. 3, mathematically, when these fuzzy inspired DNN algorithms receives the X^{FL} information, they are multiplied by an appropriate weight function, w and then summed up and the result is recalculated by an activation function, f plus a bias (+1). Mathematically, the output decision of a neuron is expressed in equation 4;

2.3 Inferencing and high-level decision-making

$$\text{Emotional state, } y = f(\sum_{i=1}^P X_{trust} W_1 + \text{bias}) \quad (4)$$

Fig. 3 How the deep neural network handles the incoming Fuzzy Likert representation to guess one's emotional state and behaviour

During this process, as shown in Fig. 2 and 4; unlike traditional explanatory modeling (Fig. 2), where the hypothetical assumptions are made between predictors using theoretical constructs, the fuzzy DNN algorithms takes a different approach. As shown in Fig. 4, it constructs its hypothesis by

Fig.4 General Deep Neural Networks (DNN) approach to modeling relationship between predictors to predict future behaviours. Retrieved from <https://developingideas.me/deepneuralnetworkoverview>

learning directly from the measurable variables of the constructs. The relationship between features (independents variables) and labels (dependent variables) are built out of simpler ones to form a graph. A graph of these hierarchies are many artificial neurons which are connected layers as illustrated in Fig. 4. In this connection, an output of one artificial neuron automatically becomes an input information to another ((Bengio, LeCun &

Fig. 5 Illustration of how mathematically, the meta algorithm uses the knowledge from Russel affect circumplex model to capture the dearth and intensity of the emotions and sentiments as a degree of truth where “1” represents full membership and “0” represents no membership.

Hinton, 2015; Deng & You, 2014; Goodfellow, Bengio & Courville, 2016; Deng et al., 2017). As shown in Fig.1, the output, $y = (y_1, y_2 \dots y_n)$ from this ensemble fuzzy inspired DNN system is a numerical decision that may be difficult for non-experts to interpret. To changed it to human language, the y information is taken as an input to the next sub-system (called TSK meta classifier). The TSK meta classifier then reason about these information using the human expert knowledge from the work of (Barrett, 1998) and Russell affect circumplex model of emotion to act and output the final emotional behaviour, $y_{predicted}$. The next section presents the working principles of the TSK meta classifier and how the final output in human language is obtained. It classifies the outcome emotional behaviour into different emotional clusters as indicated in Fig. 5. Within these clusters, it normalizes individual affective reactions into 3 classes. We called these classes, positive affective-like feelings (PA), moderate-like feelings (MODERATE/MOD) and negative affective-like feelings (NA) (see nomenclature). These responses are normalized into a fuzzy scale between 0 to 1, thus $0 \leq \mu \leq 1$. The membership degree of each emotional responses that resembles, worried-like feelings, sad-like feelings, happy-like feelings and calm-like feelings are shown in Fig.5. Within these clusters, when a respondent response with “I don’t know how I feel”, it has a membership degree of $\mu_{I\ don't\ know}(x) = 0.35 \leq \mu \leq 0.65$.

To evaluate the algorithm and demonstrate how it works in practice, in the next section, we will present a simulation experiment with a case example.

3. Simulation Experiment and Algorithm Evaluation

3.1. Dataset

We evaluated our algorithm with small dataset of 198 responses. The dataset was collected from volunteers from 15 different countries (both developed and developing countries) using the various social media platforms such as Facebook, LinkedIn including students and referral). The data was collected in different time frame.

They were observed on 25 predictors associated with 5 psychological constructs (see Table 1). These key influential predictors were elicited from the Sustainable energy technology acceptance framework of Terwel et al. (2009) and Huijts et al. (2012). These predictors are expected to help us to predict the subjects’ emotional reaction to a hypothetical CO₂ storage in geological media proposed to the subjects’ place of emotional attachment (near their homes).

Standard questionnaire from earlier studies, especially the work of Huijts et al. (2007), Midden and Huijts, (2009), Terwel et al. (2009) and Xuan and Wang (2012) were adapted to this studies to observed the participants. We contextualized the questions to their countries of origin and asked them to put themselves in a situation where the facility will be proposed near their place of emotional attachment (homes).

Table 1.

Psychological predictors used in modeling the proposed system

Competence-based trust in Government of subject country	Competence-based trust: Scientists and engineers in subject country
Competence-based trust: Industry	Integrity-based trust in Government of subject country
Competence-based trust: Environmental nongovernmental organizations (NGO)	Integrity-based trust: Industry

Competence-based trust: Environmental Protection Agency (EPA) of subject country	Integrity-based trust: Industry
Integrity-based trust: Environmental nongovernmental organizations (NGO)	Integrity-based trust: Scientists and engineers in subject country
Trust in actors as a team to store the CO ₂ in a safe and responsible way	Subject overall risk perception
Risk perception: Sudden release of large amount of stored CO ₂	Risk perception: Bad effects on trees and plants by sudden leaked of CO ₂
Risk perception: Bad effects on human health by leaked CO ₂	Risk perception: Pipeline being destroyed by earthquake
Risk perception: Bad effects on soil by leaked CO ₂	Risk perception: Acidification of sea water by leaked CO ₂
Risk perception: Pipeline been destroyed by corrosion	Risk perception: The reservoir containing the CO ₂ being destroyed by earthquake
Benefit perception: Oneself	Benefit perception: My family
Benefit perception: Future generation	Benefit perception: Environment
Reaction to Proximity of the CO ₂ Storage close to his place of emotional attachment	
Expected output: Emotional reaction to CO ₂ storage proposed to subject's place of emotional attachment	

For more details about the definition and the role of these psychological constructs in the cognitive appraisal process when people are forming attitude towards controversial energy projects, see (Huijts et al., 2007; Midden & Huijts, 2009; Terwel et al., 2009; Xuan & Wang, 2012; Yang, et al., 2016). All responses were measured on a 5 point Likert scale.

3.2. Data-preprocessing and data argumentation using the Fuzzy Likert Inference System

In line with the algorithm in Fig. 1, as a first step, we applied our rule-based Fuzzy Likert inference system to the 198 dataset to obtain its Fuzzy Likert representations, X^{FL} within a normalized closed intervals of [0,1]. This was done manually, so, it was a time consuming effort. However, in real life, it will be programmed so that the process will be done automatically immediately a subject report his or her behaviour. After the pre-processing of the Likert data, we applied a 60/40 rule and randomly divided these original datasets into training dataset and testing dataset. As mentioned in the preceding section, the merit associated with the conversion is that it provides a high dimensional behavioural space where one can perform data argumentation using the training dataset. In this way, one can collect big experimental dataset to augment the original training dataset. Using this technique, 72,105 experimental datasets were collected to augment the original dataset to build three fuzzy inspired deep neural networks which is the goal of the next section.

3.3. Building the ensemble fuzzy rule-based deep neural networks system

We implemented the fuzzy inspired deep network algorithm in Keras with Google TensorFlow backend. In line with Bengio (2012) recommendation, we experimented different hyper-parameters associated with the model and the optimization. Table 2 therefore presents the architecture that best models the structure of our datasets in relation to the problem under investigation.

Table 2

Experiments settings

Learner type	Neural networks
Number of output nodes	5 classes → [0,1] on a fuzzy scale
Loss function	Categorical cross-entropy
Hidden layer	Model 1 is a 12 Layer network (including input and output layer) with 11 hidden layers each for 3 models. Model 2 and 3 is a 11 layer network with 10 hidden layers
Maximum number of training iterations	Model 1:200 epochs, Model 2: 200 epochs, Model 3:200 epochs,
Activation function	Rectified linear unit (ReLU)
Optimization Algorithm	Stochastic gradient descent
Learning rate	0.003
Early stopping rule	Manual stopping by observation in loss in generality
Pre-training	No pre-trained model. The models were trained from scratch
Regularization	Dropout
Dataset for testing: objective evaluation	84 random sample hidden from the 3 models
Learner type	Neural networks
Regularization	Dropout

In terms of depth of the network, as one of the fathers of deep learning, Bengio recommended that there are not a one-size fits all solution. For example, in a Quora forum discussion on this issue on May 8, 2013, when someone asked the question about the depth of the network this was his response, “*Very simple. Just keep adding layers until the test error does not improve anymore.*” In line with Bengio recommendation, we experimented with different neurons and depth and as indicated in the experimental setting, we arrived at 11 hidden layers for Model 1 and 10 hidden layers for Model 2 and 3. To prevent overfitting, we introduced dropout in the architecture as indicated in Table 2. Using this experimental setting, we built three deep models to predict an emotional reaction to CO₂ storage. Table 3 shows their validation accuracies.

Table 3.

Results from Experiment 1: Validation accuracies of the three base models after training

Model name	Number of out-of sample for training	Rule of data split during training	Rule of data split: validation	Validation accuracy
Model 1	72,105	60%	40%	99.9%
Model 2	72,105	60%	40%	97.03%
Model 3	72,105	60%	40%	99.5%

In line with the algorithm as indicated in Fig. 1, the predicted values of model 1, 2 and 3 were then used as inputs argument to build a TSK meta classifier. The goal is to obtain the average of fuzzy interpretation of the decision from the ensemble deep models. This meta classifier was then applied to the 84 testing dataset hidden from the three models to offer an objective evaluation of the algorithm to gain insight into its generalizability capability irrespective of their validation accuracies. This testing dataset is not processed data (augmented data). It is raw from the respondents.

Running the simulation, Table 4 presents the prediction and the expected target.

Table 4.

Experimental result showing the comparison between the predicted value and the expected target

Target	Predicted	Target	Predicted	Target	Predicted
NA	NA	PA	PA	NA	NA
MOD	NA	NA	PA	NA	NA
NA	MOD	PA	NA	NA	NA
NA	NA	NA	NA	NA	NA
NA	PA	NA	NA	PA	NA
NA	NA	NA	NA	PA	PA
MOD	PA	PA	NA	NA	NA
NA	NA	NA	NA	NA	NA
MOD	MOD	NA	NA	PA	PA
NA	NA	NA	NA	PA	PA
NA	NA	PA	PA	NA	NA
PA	PA	NA	NA	NA	NA
NA	NA	PA	PA	NA	NA
NA	NA	MOD	MOD	NA	NA
NA	NA	PA	PA	PA	PA
NA	NA	NA	NA	PA	PA
NA	NA	NA	NA	NA	NA
NA	NA	MOD	MOD	NA	NA
NA	NA	NA	NA	NA	NA
PA	PA	NA	NA	NA	NA
NA	NA	NA	NA	NA	NA
NA	NA	NA	NA	NA	NA
PA	PA	NA	NA	NA	NA
PA	PA	NA	NA	NA	NA
NA	NA	PA	PA	NA	NA
NA	NA	NA	NA	PA	PA
MOD	MOD	MOD	MOD	MOD	MOD

In the next section, we will present the interpretation of the result. The concluding remark of the paper is also given to highlight the ethical dimension of the algorithm and limitation of the proposed system.

4. Discussion and Conclusions

4.1 Interpretation of the results

In this paper we have proposed the use of an emotional artificial intelligence (AI) algorithm an alternative for improved modelling and prediction of the participants' emotional behaviour towards controversial energy projects to guide policy and company's decision-making. Our method harnesses the power of artificial intelligence to infer the future subjective emotional behaviour from the stakeholder' cognitive thinking process based on their cognitive appraisal of the energy project. To validate this method, we investigated it in the context of emotional responses to a hypothetical CO₂ storage technology. As illustrated in Table 3, we validated the algorithm with 40% of the 72,105 experimental datasets and obtained an average validation accuracy of 98.81%. We then challenged the algorithm further and proceeded to evaluate it generalizability to unseen cases. Using 84 raw dataset from a primary research, we applied the algorithm to these unseen self-reported cases. As indicated in the experimental results, out of 84 unseen cases, the algorithm successfully predicted 75 correctly with 9 mistakes as indicated in Table 4. In the experimental result in Table 4, NA indicates respondents who were worried and expressed unpleasant feelings

of having the CO₂ Storage close them. Those who expressed pleasant feelings and were not worried about having the CO₂ Storage close to them are indicated with PA. Those who expressed mix feelings are also indicated with MOD.

The result obtained above adds to the existing knowledge that human human's emotions on energy projects predictable in line with Lazarus, 1991 and Barrett (2017). Beyond this evidence, a key question is, what is the scientific and societal value of the method we have proposed? This is the discussion in the next section. It starts by first taking the reader through the challenges associated with the self-report emotion measure and ends with how our proposed method can add value to overcome.

4.2 Theoretical and practical Implication of the model

Addressing emotion related behaviour to retain social licence for an energy project requires long term stewardship. It is not a commitment that ends after the project has been approved. It spans throughout the project's life cycle. This is due to the dynamic nature of social license and how behavioural changes and changes of events over time may lead to different emotional responses (Wilson & Gilbert, 2003; Barrett, 2017; Gough et al., 2018). In ensuring this stewardship attitude in practice, the self-reported emotion measurements approach used in this process to understanding the feelings of the people can loosely be grouped into one of two strategies, either direct communication and engagement, or indirect communication and engagement strategies.

In the direct engagement strategy, project managers may go to the field and engage with citizens and other important stakeholders such as the civil society organizations, local authorities, and other concerned stakeholders. For example, in the case of CCS in soliciting the public opinion, Ashworth et al (2011) organised a workshop with practitioners. In this communication and engagement task, project developers used paper and pencil or small group discussion methods for the stakeholders to self report their feelings and share the results with participants and project developers. As we highlighted in the introductory section, this method of survey was not free from social desirability bias. Participants may not have answered truthfully if they perceived their response to be socially undesirable. It is plausible that in cultures where the balance of power or political pressure impacts the individual's decisions and behaviour that some people may not be willing to share their true feelings. This may happen if the project developers involved in the project workshop are powerful individuals who can influence the social life of local communities. Avelino (2011) found that the social agent(s) who failed to express their true feelings were likely to anonymously leverage this true feeling in collective action. This may occur if she/he had the opportunity to express his/her true feelings to either support or stop a project if the agent of the collective action (e.g advocacy group) value-set matched his/her own value-set.

On other projects, the manager may employ indirect communication strategies. Since the project requires a long-term commitment, the direct form of engagement may become boring or resource intensive over time. When this happens, some project developers may give up on it and continue with the project with less or no engagement with the community. As energy practitioners, we have witnessed this in a few countries with the implementation of small-scale energy projects. This situation occurred in some developing countries on the African continent and in Asia. Through technology and knowledge transfer, after implementation, the project was entrusted to the stewardship of the local managers. As time passed, this stewardship attitude diminishes for several reasons, including a lack of motivation or resources to manage the project well. This lack of stewardship risks the project's sustainability due to the fragile nature of social licence as new emotional behaviours are triggered over time. If this

happens, the local citizens may become dissatisfied with the project when its existence begins to negatively impact the community. Dissatisfaction can potentially lead to protest actions against the energy technology project.

As social licence is a critical component of a project's success over time, we wondered how the traditional direct approaches could be improved and managed without becoming tedious, time consuming, and expensive for project developers. In addition, we wanted to know how social desirability bias could be minimized, while giving the citizens a voice to express their true feelings freely. These became the driving questions of our study.

In the literature, practitioners and scientists usually use the indirect approach using surveys that distant themselves from the stakeholders. Even in the novel work of Ashworth et al (2011), this approach was suggested to practitioners in addition to the direct engagement. Sample questions to ask are provided. Using this survey-based self report emotion measurement, (Ciuk & Troy, 2015) findings showed that the strategy's strength was that it was relatively inexpensive and efficient. It reduced social desirability bias because the people could freely self-report their true feelings without being intimidated, especially when anonymity was guaranteed in the survey. Unlike the face-to-face self report measurement that relied on small groups and a few workshop participants, large audiences could be reached in few days, especially when the project developers took advantage of social media and the participants' vast access to mobile phones links. For example, this indirect self-report engagement strategy was the method used in the 2011 European Union (EU) Special Eurobarometer on public awareness and acceptance of CO₂ capture and storage..

Despite this method's merit, the challenge for investigators is how to manage the huge amount of information (thus process and analyse) received and figure out the feelings of the people who were surveyed. For example, if one observed the Eurobarometer reports, the researchers and practitioners (TNS Opinion & Social network) reported that they interviewed 13091 EU citizens in 12 Member States of the European Union from February to March 2011. The report was ready in May 2011. On average, it took approximately four months to know what their stakeholders in the 12 member states countries thought about the energy innovation under investigation.

Earlier studies found that data collection and analysis needed to be done quickly to accurately be used to predict behaviour related to events that evokes emotions (Wilson & Gilbert, 2003). Human emotion changed quickly and was often based on how it processed new information from the surrounding environment (Barrett, 2017)

One can infer from the findings of Wilson & Gilbert (2003) and Barrett (2017) that the information people have spent resources to collect can become obsolete based on the events and behaviours they are currently observing. This issue of obsolescence is a critical factor when considering how project managers can prevent the loss of social licence in the community. The faster the data can be collected and analysed, the better the project manager can respond to negative emotional factors before emergent events can change people's minds. In the Eurobarometer CCS case, the practitioners and the researchers themselves conceded to the findings of (Wilson & Gilbert, 2003) and (Barrett, 2017). They wrote, "It is worth noting that the fieldwork for the data collected for this survey was undertaken before the earthquake in Japan on 11 March 2011. The resultant radioactive emissions from the Fukushima nuclear power plant could have influenced respondents' attitudes towards nuclear energy as an energy source had the fieldwork taken place after the earthquake." (Eurobarometer report on CCS, 2011, p. 7).

Roeser (2011) conducted a study the same year after the Fukushima nuclear power plant incident. It supported the Eurobarometer (2011) observations. For example, Roeser reported that after the incident, many people were wondering whether nuclear energy was really a wise option. She wrote, "Germany immediately shut down several nuclear reactors, and the German Green Party achieved unprecedented results in the local elections due to its anti-nuclear position." (p.197). This action showed that the observation of the Eurobarometer CCS reviewers may have been accurate in concluding that the incident influenced the stakeholders' view. If the survey had been taken at a different time, their attitude towards Nuclear Energy might have been different.

Gough et al (2018) noted similar observations. Observing their participants' trust level in establishing social licence, our colleagues wrote that "results show that perceptions of trust and confidence in key institutions to safely manage projects are highly dependent not just on the track record of the organisations, but are strongly influenced by past experiences with different technologies" (p.16). Agreeing with Barrett (2017), this study suggests that if the fieldwork had taken place after the earthquake, some of the stakeholders might have compared the characteristics of Nuclear Energy and waste disposal to CCS and disposal of CO₂. This may have influenced their emotional view and perceptions. Last but not least, challenges associated with traditional data analysis in both approaches are its potential lack of objectivity and transparency due to satisfying their sponsors' agenda in the project research. According to Nahrin, (2015) this usually happens because "contemporary research has moved away from a 'research-led model' to 'customer-contracted model' where the research is conducted through projects commissioned by the funders. In the customer-contracted model, the customer/ client/ funder reserves the right about what to investigate, reducing the control of the researcher over choosing the research agenda. It means that sometimes, institutions with economic power have control over the production of knowledge (p. 3)."

All the challenges associated with the self-report measurements approach are what makes the emotional intelligence algorithm we are proposing novel in the field and in practice. We believe this method to be a superior model for several reasons.

First, in data handling, unlike proponents and opponents' experts' subjective decisions that aligned to their missions, our algorithm operate differently. It favours no one (neither proponent nor opponent actors), assuming that the creators of the system were not bias in their design. The model is automated and can manage the stakeholders' behaviours throughout the project life cycle without becoming burdensome for the project developers. In the management of stakeholders, it limits the human actors' influence since it extracts the information directly from the stakeholders. Using this information, it communicates what it reported in the data, not what the expert proponents and opponents expect to see. The researchers cannot subjectively manipulate the information to lobby for policy mechanisms that follow their own agendas to reject or facilitate the CCS projects.

Second, our algorithm has speed and knowledge despite its lack of human wisdom. This lack of human wisdom is why we will not recommend it as a replacement for the human experts' tasks. It can be implemented as an integral part of the communication and engagement process. In terms of time between data acquisition and analysis results, the algorithm can collect data and analyse it simultaneously. It accomplishes this task in real time within a few seconds as each bit of data information comes into the system. This save human experts time and effort compared to previous surveys' analysis that took days or months to accomplish. For example, in our simulation experiment, it took the algorithm approximately 6 seconds to detect the emotions of the 84 test participants.

As illustrated in Fig. 1 in terms of information acquisition, measurement, and processing, project developers can take advantage of digitalization and the astounding availability of mobile phones in the world today. The model can be implemented in the form of an intelligent app. This app can be launched in the cloud and can be accessed on mobile phones and other devices as shown in the picture with the girl (User 1). In this case, the project researchers can reach out to large audiences in a short time in the comfort and privacy of the participants' homes, unlike the direct self-report measurement. The developer can even make it more engaging for people to use by converting the X input variable in Fig. 1 into an interactive voice system, similar to Apple Siri, engaging the people in a two-way conversation.

The project managers will need to be certain that the ethics of the app is well explained due to data privacy laws. This transparency in data ethics is important because in actual use, the more it interacts with people, gathering data on their emotions and perceptions about the energy project, the more intelligent it becomes. In terms of time, it does not matter how much information is received at any one moment. Even if only one response comes into the system, the program will still analyse and change trends in the prediction as more information is gathered. This is communicated by the system to decision-makers in real time, as indicated with User 2 in Fig. 1. If the project developers want to be even more transparent, they can give policymakers a guest access to see the views of the people on their project already collected in the system. They can also see the trends in emotions and sentiments in real time as visualizations, depending on how they want to share the information with interested decision-makers.

Another interesting thing about the algorithm is that, while the passing of time means potential data obsolescence in the conventional methods of data collection, time means intelligence in our system. In practice, it means that the more the algorithm is exposed to new information and compared to old information, the more it retrains itself on its existing knowledge and re-adjusts its decision using Equation 4. This retraining and optimization makes it to become more accurate in its predictions. The theoretical implication of this improved intelligence is that, over time, this project manager will be attuned to the stakeholder's emotional related beliefs and behaviours related to the energy project and be prepared to handle them proactively. The implication is that scientists can collaborate with the practitioners to harness this machine intelligence to predict new behaviours that has not yet been observed in the field. The new insights may contribute to developing and testing new theories that refine existing theories and assumptions, progressing the field with implications for practice as recommended by Shmueli (2010).

4.3 Concluding Remarks

In conclusion, despite the strengths of our method in overcoming the limitations of the self-report emotion measurements, it is not without its own limitations. We did find, in a sensitivity experiment, that it was challenging for the algorithm to predict indecisive feelings. In our subjective opinion, it seems natural to us that people that are indecisive are more unpredictable and something that a model cannot fix. We will not draw that conclusion yet, and will leave for future studies. The method we tested is adaptable to study emotional responses to other projects, including Wind Energy, Nuclear Energy and Hydrogen Technology since Huijts et al., (2012) found that it share similarities in cognitive variables people use in appraising the technology. We recommend future studies replicating our findings in these alternative energy technologies

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Appendix

Raw data linked to the article.

REFERENCES

- Ashworth, P., Bradbury, J., J., F. C. F., Greenberg, S., Hund, G., Mikunda, T., . . . Shaw, H. (2011). Communication/Engagement Toolkit for CCS Projects, Communication/Engagement Tool Kit for CCS Projects. Energy Transformed Flagship, National Flagships Research, Commonwealth Scientific and Industrial Research Organisation (CSIRO).
- Breiman, L. (2001). Statistical modeling: The two cultures. *Statist. Sci.* (16).
- Cózar, J., Ossa, L. D., & Gámez, J. A. (2017). Generation of first-order TSK rules based on the apriori + search approach. *IEEE Congress on Evolutionary Computation (CEC)*, 1675-1682.
- D., B. (2017). An approach to explainable deep learning using fuzzy inference. *NextGeneration Analyst V. International Society for Optics and Photonics*.
- Deng, Y., Ren, Z., Kong, Y., Bao, F., & Dai, Q. (2016). A Hierarchical Fused Fuzzy Deep Neural Network for Data Classification. *IEEE Transactions on Fuzzy Systems*. 11(10), 1109.
- Deng, L., & Yu, D. (2014). *Deep Learning: Methods and Applications*, The Netherlands, Delft: Now.
- Deng, Y., Bao, F., Kong, Y., Ren, Z., & Dai, Q. (2017). Deep direct reinforcement learning for financial signal representation and trading", *IEEE Trans. Neural Netw. Learn. System*. 28(3), 653-664.
- Feldman Barrett, L. (2017). *How emotions are made: the secret life the brain*. New York, NY: Houghton-Mifflin-Harcourt. .
- Feldman Barrett, L. (1998). Discrete emotions or dimensions? The role of valence focus and arousal focus. *Cognition and Emotion*. 12, 579-599.
- Goodfellow, I. (2016). *Deep learning*. Book in preparation for MIT Press (www.deeplearningbook.org).
- Gough, C., Cunningham, R., & Mander, S. (2018). Understanding key elements in establishing a social license for CCS: an empirical approach, *International Journal of Greenhouse Gas Control*.
- Huijts, N. M. A. (2018). The emotional dimensions of energy projects: Anger, fear, joy and pride about the first hydrogen fuel station in the Netherlands. *Energy Res. Soc. Sci.*, 44, 138-145.
- Huijts, N. M. A., Midden, C. J. H., & Meijnders, A. L. (2007). Social acceptance of carbon dioxide storage. *Energy Policy*. 2780-2789.
- Huijts, N. M. A., Molin, E. J. E., & Steg, L. (2012). Psychological factors influencing sustainable energy technology acceptance: A review-based comprehensive framework. *Renewable and Sustainable Energy Reviews*. 16(1), 525-531.
- IEA. (2010). *Technology Energy Perspectives: Scenarios & Strategies to 2050* Paris, France. 710.
- IEA. (2013). *Technology Roadmap: Carbon capture and storage*, OECD/IEA, Paris.
- IEA. (2016). *20 Years of Carbon Capture and Storage*. International Energy Agency.
- Janhunen, S. (2018). *Determinants of the local acceptability of wind power in Finland* (Doctoral dissertation). Retrieved from <http://lutpub.lut.fi/bitstream/handle/10024/157262/Sari%20Janhunen%20A4.pdf?sequence=1&isAllowed=y>

- Lazarus, R. (1991). *Emotion and adaptation*. New York: Oxford University Press. Google Scholar.
- LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature* 521, 436-444.
- Li., Q. (2013). A novel Likert scale based on fuzzy sets theory, *Expert Systems with Applications*. 40(5), 1609-1618.
- Midden, C. J. H., & Huijts, N. M. A. (2009). The role of trust in the affective evaluation of novel risks: The case of CO2 storage. *Risk Analysis*. 29, 743-751.
- Naimi, A. I., & Balzer, L. B. (2018). Stacked generalization: An introduction to super learning. *Eur. J. Epidemiol.* . 33, 459-464.
- Paulhus, D. L., & Reid, D. B. (1991). Enhancement and denial in socially desirable responding. *Journal of Personality and Social Psychology*, 60(2), 307-317.
- Perlaviciute, G., Steg, L., Contzen, N., Roeser, S., & Huijts, N. (2018). Emotional responses to energy projects: Insights for responsible decision making in a sustainable energy transition. *Sustainability*. 10(7). doi: 10.3390/su10072526
- Posner, J., Russell, J. A., & Peterson, B. S. (2005). The circumplex model of affect: An integrative approach to affective neuroscience, cognitive development, and psychopathology. *Development and Psychopathology*. 17, 715-734.
- Roeser, S., & Pesch, U. (2016). An Emotional Deliberation Approach to Risk. *Science, Technology, & Human Values*, 41(2), 274-297.
- Roeser, S., Philos., & Technol. (2011). Nuclear Energy, Risk, and Emotions. *Philosophy Department, University of Twente, Enschede, The Netherlands*, 24, 197.
- Russell, J. A. (1980). A circumplex model of affect. *Journal of Personality and Social Psychology*. 39(1161-1178).
- Shmueli, G. (2010). To explain or to predict. *Statistical Science*. 25, 289-310.
- Symeonaki., M., & Kazani., A. (2011). Developing a fuzzy Likert scale for measuring Xenophobia in Greece, *ASMDA, Rome, Italy*. 7-10.
- Terwel, B. W., Daamen, D. D. L., & Ter Mors, E. (2013). Not in my backyard (NIMBY) sentiments and the structure of initial local attitudes toward CO2 storage plans. *Energy Procedia*. 37, 7462-7463.
- Wallquist, L. (2011). *Public Perception of Carbon Dioxide Capture and Storage*. Switzerland: ETH ZURICH. Doctoral dissertation.
- Welte, J. W., & Russell, M. (1993). Influence of socially desirable responding in a study of stress and substance abuse. *Alcoholism: Clinical and Experimental Research*, 17(4), 758-761.
- Wilson, T. D., & Gilbert, D. T. (2003). Affective forecasting. In M. P. Zanna (Ed.), *Advances in experimental social psychology* 35(345-411).
- Wolpert, D. H. (1992). Stacked Generalization. *Neural Networks*, Vol. 5, pp. 241-259, Pergamon Press.
- Xuan, Y., & Wang, Z. (2012). Carbon capture and storage perceptions and acceptance: A survey of Chinese university students. *International Proceedings of Computer Science Information Technology*. 38(100).
- Yang, Lin, Zhang,Xian& McAlinden,Karl J.(2016). The effect of trust on people's acceptance of CCS (carbon capture and storage) technologies: Evidence from a survey in the People's Republic of China,*Energy*, Volume 96, 2016,Pages 69-79,ISSN 0360-5442, <https://doi.org/10.1016/j.energy.2015.12.044>.
- Zadeh, L. (1965). Fuzzy sets. *Information and Control*. 1965; 8: 338–353.