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A fuzzy knowledge-based system for UV exposure management

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***Abstract*—Ultraviolet (UV) radiation is part of the optical spectrum of the solar light. Exposure to ultraviolet radiation for prolonged periods of time can cause damage to skin cells and lead to the development of both non-melanoma cancer and melanomas. Workers in constructions sites are particularly susceptible to exposure in UV radiation due to the prolonged periods of staying in outdoors areas that offer no protection from the sun rays. This paper presents a fuzzy logic system that monitors the UV levels at particular construction sites, the environmental conditions that can affect UV as well as the location of workers and can provide notifications and alerts to both the workers and health and safety managers at each site.**

***Index Terms*—Adaptive expert systems; UV exposure; Fuzzy multi-criteria analysis; IoT; Data analysis**

I. Introduction

Sunlight is part of the electromagnetic radiation that is emitted from the sun and propagates through space before reaching the earth. The optical spectrum of the solar light includes infrared light, visible light and ultraviolet (UV) radiation as well as heat, with a wavelength ranging from $100nm$ to $400nm$. These components of the solar spectrum are referred to as optical radiation. The biological effects of UV radiation vary significantly with wavelength and thus UV is commonly classified into three bands; UVA, UVB and UVC. UVA has a wavelength between 315 to $400nm$, UVB $280nm$ to $315nm$ and UVC $100nm$ to $280nm$. UVC and most of UVB radiation are filtered by the atmosphere and the ozone layer, therefore almost all of the UV radiation that reaches earth is UVA.

Limited absorption of UV radiation has benefits to humans, including the production of vitamin D3 that is vital for musculoskeletal health. However, an increased exposure can cause several acute or long-term health effects; It can result in inflammation of the skin and contributes to skin ageing and wrinkling, as well as cause cataracts and immune system damage. Moreover UV radiation is genotoxic and a known carcinogen, leading to different forms of skin cancer, through the accumulation of mutations caused by UV damage [1]. In fact, melanoma and nonmelanoma skin cancer are the most common types of cancer in white populations [2]. The World Health Organization reports approximately 1.5 milion cases of skin cancer in 2020 due to exposure to UV radiation.

The ASSIST-IoT EU project focuses on the design, implementation, and validation of an open, decentralized reference architecture, associated enablers, services and tools, to assist human-centric applications in multiple verticals. One such vertical involves the safety of workers in construction sites and aims to increase their occupational safety and health at their complex and unpredictable work environment.

The work of this paper is focused on one vector of occupational health, the monitoring and decision making associated with the exposure of workers in construction sites to erythemally weighted UV irradiance, with the introduction of a knowledge-based system. The workers' location is constantly tracked with the use of smart IoT devices and together with environmental data on UV radiation levels, effective decisions can be made, emulating the human decision making process.

The paper is structured as follows: Section II details past research on fuzzy knowledge-based systems as well as on intelligent UV radiation protection systems. Section III presents the architecture of the proposed knowledge-based system. Section IV discusses the concept of fuzzy sets and details the fuzzy knowledge modelling of the system. Finally, Section V provides details on the implementation of an instance of the proposed knowledge-based system for personalized UV exposure management and decision making.

II. Related Work

A growing number of studies on knowledge-based systems has been published, although research on the use of such systems for UV exposure management is limited. A supervised knowledge-based decision support system for use in railway operation control systems is detailed in [3]. The system is based on dispatching experts knowledge, modelled as a series of fuzzy "IF-THEN" rules. The rules are visualized and represented in a Fuzzy Petri Net notion to allow for the easier design and maintenance of the knowledge base. Uricchio, Giordano and Lopez [4] present a supervised knowledge-based system that uses expert knowledge formalized as a set of fuzzy rules to evaluate the environmental impact of human activities on the quality of groundwater. A similar system is used in [5] on a completely different area of research; the economic analysis of RFID investment using a cost/benefit analysis. A fuzzy knowledge-based system is used to calculate the expected revenue increase due to the use of RFID tags in a distribution centre, while the expected net present value of the investment is simulated using a Monte Carlo method. Giordano and

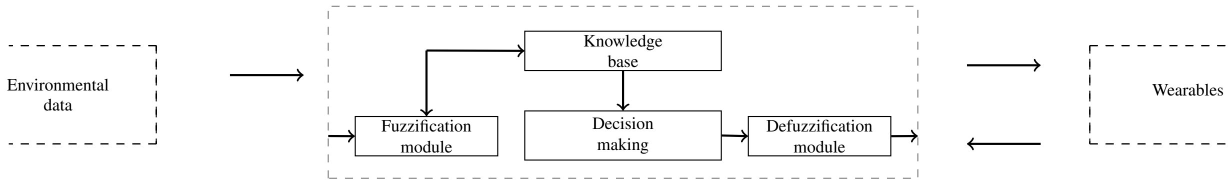


Fig. 1. Architecture of the proposed knowledge-based system

Liersch [6] use a fuzzy knowledge-based system together with a GIS interface to support soil salinity monitoring.

Significant research also exists on intelligent UV exposure management systems. Tsantarliotis et al. [7] propose a system that delivers intelligent indications for sun radiation protection. The purpose of this system is to fill the gap of personal solar protection in a novel way, by computing a tailored index of solar dangers linked with the user and the surrounding environment. The system is divided into two parts: a sensing device that detects solar radiation in real time and an application that interprets the data from the sensory equipment. The program analyzes the user's attributes and solar radiation data to calculate the recommended periods of safe exposure in direct sunlight. Correa [8] present UVBoost, a hybrid model that integrate the accuracy of a Radiative Transference Model (RTM) with the efficiency of ML CatBoost. UVBoost is made up of a robust, detailed, and accurate database provided by an RTM, used to train the regression model and allow for the estimation of surface ultraviolet radiation (UVR) using sun position, Total Ozone Content and Aerosol Optical Depth as independent predictive variables. The authors simulate daily UVR at eight distinct sites across the world. The results reveal that UVBoost is highly effective at replicating cumulative UVR doses over the day, with minor variations. Nielsen et al. [9] simulate the transmission of solar radiation through the skin by merging a bio-optical model of human skin with advanced radiative transfer theory. The computed optical features of the skin are subsequently paired with action spectra of various photobiological processes to create efficiency spectra for different skin types. The authors demonstrate that the interaction of solar radiation with skin exhibits significant temporal fluctuations as a result of dynamic changes in the optical characteristics of the skin caused by solar radiation. Oh et al. [10] present a mobile deep learning system that estimates UVI based on illuminance data acquired from mobile devices at the users' location. The suggested technique examines the relationship between illuminance and UVI using the natural light DB gathered by real-life measurements. The suggested technique allows for the delivery of UV information to users through smart devices with illuminance sensors, even in the absence of UVI measurement equipment. When the experiment results are compared to that of the spectrometer, it is shown that the suggested approach can provide UV information with an accuracy of $90 - 95\%$.

III. System Architecture

The system presented in this paper is a Fuzzy Logic Device (FLD). It is the result of mapping deterministic inputs, starting from a set of rules relating linguistic variables to one another using fuzzy logic. For the mapping to be performed, deterministic values are converted into fuzzy values, and vice-versa [11]. As depicted in Figure 1, the proposed FLD consists of four main modules; fuzzification, knowledge base, decision making and defuzzification.

Environmental data on UV levels, cloud coverage, ozone levels, time of year and time of day are fed into the system by an external service. Location data of construction site workers are provided to the proposed FLD through the use of IoT wearables. Personalized information on the skin type of each individual as well as the SPF of any sun protection used is also available for each worker.

The data input is received by the FLD as crisp numerical values instead of fuzzy sets. For this reason, a fuzzification module has been introduced, being responsible for the mapping of such values to fuzzy sets. The resulting sets can be used in turn to activate all relevant rules by calculating their membership functions. The knowledge base is the process model of the system. It consists of a database that contains the rule structure for each different construction site, containing information about the site's layout, covered areas and the relevant materials (e.g., trees, completed buildings etc.) that affect the reflection of the UV radiation and the denseness of the shadow (i.e., the protection it will offer to the worker).

The fuzzy rules, together with the input from the fuzzification module are combined to generate output by the decision making module. The defuzzification module aggregates the rule consequents, and selects the highest-rated to produce a crisp output as the outcome of the FLD.

The output of the defuzzification module is forwarded to the IoT wristbands of the construction workers, to notify them of prolonged exposure to UV radiation. The information is augmented with operational information in a clear and logic way. The next section details extensively the methodology used for the implementation of the proposed FLD.

IV. Fuzzy knowledge modelling

In a real world scenario, information can be affected by uncertainty. Then, it is often not easy or desirable to group pieces of information into crisp sets (sets with a binary membership where objects are either members of the set or not) based on precise parameters. Instead, fuzzy sets can be used for information classification based on imprecise criteria.

Let us consider for example the monitoring of workers in a construction site for UV exposure by a health and safety manager. The manager analyzing the radiation levels will not, in most cases, be able to determine whether they have exceeded the threshold for the creation of erythema, as it depends on many factors, such as the skin type of each worker, the sunscreen, the levels of cloud coverage or whether they work in a shared area (e.g., a completed part of the building). Instead, it may be inferred whether a worker is exposed to *too much* or *too little* UV radiation.

The fuzzy set theory was first introduced in the seminal paper by Zadeh [12] as an extension of classical fuzzy models. A fuzzy set is a collection of objects that don't have explicitly defined criteria of membership. Instead of a binary membership (i.e. 0 or 1) to a set, each object has a grade of membership $\in [0, 1]$ instead, that indicates its degree of truth in a subjective way. In other words its degree of membership indicates how that object "fits" into the set.

In complex emergency management scenarios, there are two distinct types of problem knowledge that can usually be inferred for a situation, *objective knowledge* and *subjective knowledge* [13]. Objective knowledge refers to quantitative variables that can be used to accurately represent information. Subjective knowledge on the other hand corresponds to usually not-quantifiable knowledge in the form of verbal statements - *If you have been exposed to too much UV radiation, find a shaded area*. Obtaining objective knowledge for a specific event, area or situation though is not easy and can often be inaccurate or not applicable; many times gaining subjective knowledge through the interaction with experts is better suited to capture the imprecise modes of reasoning that is essential for the ability of people to make decisions in an uncertain environment [14]. This type of linguistic information is close to the human cognitive processes, more reliable, and better informative for the progress of the decision making problem [15].

This paper uses both types of information to create fuzzy antecedent-consequent "IF-THEN" rules that can be used to propose different courses of actions. One such example that describes a straightforward course of action is - *If workers are exposed to increased levels of UV radiation for a prolonged period of time, guide them to a shaded area*. In this example, the notion of *increased levels of UV radiation* is a linguistic variable that forms the antecedent part of the rule and can have a different meaning in different settings. The notion of *guide them to a shaded area* represents a crisp course of action and is the consequent part of the rule.

A rule R_i can be formally expressed as follows:

$$R_i(w_{R_i}) : \text{IF } \underbrace{P \text{ is } \mu_P}_{antecedent} \text{ THEN } \underbrace{A \text{ is } a}_{consequent} \tag{1}$$

The problem is to infer the consequent A is a from the antecedent P is μ_P. Every rule R_i is associated with a rule weight $w_{R_i} \in [0, 1]$, that is determined from feedback provided by site experts. The weight of the rule corresponds to the degree of truth of its statement. The precondition P is a linguistic variable characterized by an appropriate degree of membership $\mu_P \in [0, 1]$ to a particular fuzzy set. The degree of membership of P reflects the subjective willingness to accept it as a member to some set S [16]. A value of μ_P equal to unity indicates a strong membership of P to S while a value of zero indicates a strong rejection from S. The consequent part of a rule consists of an action A that defines its outcome. It is associated with a degree of confidence $a \in [0, 1]$ and is a linear combination of the rule's inputs - it is therefore proportional to both the degree of membership of the rule's precondition and the rule's weight. Given a degree of membership μ_P of a precondition and a weight w_{R_i} of a rule, the action confidence a can be computed as:

$$a = \mu_P \times w_{R_i} \tag{2}$$

A rule can also consist of multiple preconditions $P_1, \ldots, P_n$ from fuzzy sets $S_1, \ldots, S_n$:

$$R_i(w_{R_i}) : \text{IF } \underbrace{P_1 \text{ is } \mu_{P_1} \ldots \text{AND } P_n \text{ is } \mu_{P_n}}_{antecedent} \text{ THEN } \underbrace{A \text{ is } a}_{consequent} \tag{3}$$

To determine the membership function of the intersection of the fuzzy sets in the antecedent, the fuzzy AND operator can be used since it is implied that the intersection corresponds to the AND in human thinking [17]. For two preconditions, P_1 and P_2, their intersection μ can be expressed as P_1 AND P_2 and is defined as:

$$\mu = \gamma \times MIN(\mu_{P_1} + \mu_{P_2}) + \frac{(1-\gamma)(\mu_{P_1} + \mu_{P_2})}{2} \tag{4}$$

The parameter γ indicates the degree of nearness to the strict logical meaning of AND [18]. This paper uses a value of $\gamma = 0$, reducing equation (4) to the arithmetic mean of sets S_1 and S_2, however experimentation with different values of γ can be also performed.

To combine multiple rules with the same action a_i, a_j, the fuzziness reduction method introduced in [19] is used. For two actions, A_1 is a_1 and A_2 is a_2, the method is defined as:

$$a = t_1 \times MAX(a_1, a_2) + t_2 \times (a_1 + a_2 - a_1 \times a_2) \tag{5}$$

where $t_1, t_2 \in [0, 1]$ and $t_1 + t_2 = 1$. The aggregated value is a combination between $MAX(a_1, a_2)$ and $(a_1 + a_2 - a_1 \times a_2)$ with the support for each of the operators being controlled by parameters t_1 and t_2. For the proposed FLD, the values $t_1 = t_2 = 0.5$ were used.

From a top-down perspective, the knowledge-based system of this paper can be represented as an adaptive network, a multi-layered feed-forward network of nodes that are connected through directional links [20]. Each of the nodes performs a specific function on some input using a formula and generates the appropriate output. Some of the nodes have different input parameters that affect their output, and these

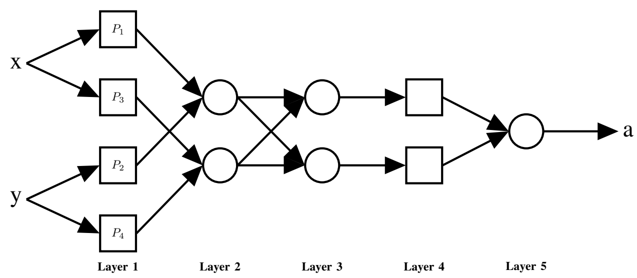


Fig. 2. The proposed FLD as an adaptive network

parameters can *adapt* based on feedback from experts from each construction site. For easier identification, these nodes are visualized as squares. Fixed nodes are drawn as circles instead.

Figure 2 presents an example of such a network for two fuzzy rules R_1 and R_2, associated with weights w_{R_1} and w_{R_2} respectively. Both rules have as an input the numerical values x and y (i.e. *time of day, cloud coverage*). Rule R_1 then has as an antecedent the linguistic variables P_1 and P_2 (i.e. *too hot, extended exposure*) and as a consequent the action A_1, while rule Rule R_2 has as an antecedent the linguistic variables P_3 and P_4 and action A_2 as a consequent. Rule 1 has the form of $R_1(w_{R_1})$: IF P_1 is $\mu_{P_1}(x)$ AND P_2 is $\mu_{P_2}(y)$ THEN A_1 is a_1. Rule 2 has the form of $R_2(w_{R_2})$: IF P_3 is $\mu_{P_3}(x)$ AND P_4 is $\mu_{P_4}(y)$ THEN A_2 is a_2.

- Layer 1: Every square node of this layer calculates the membership functions $\mu_{P_1}(x)$, $\mu_{P_2}(y)$, $\mu_{P_3}(x)$ and $\mu_{P_4}(y)$ for P_1, P_2, P_3 and P_4 respectively based on input x and y, to determine the degree of truth of the preconditions. The membership functions can be any bell-shaped functions, such as Gaussian but for the proposed FLD, the following function from [20] is used:
$$\frac{1}{1+[(\frac{x-c_i}{a_i})^2]^{b_i}} \tag{6}$$
where $\{a_i, b_i$ and $c_i\}$ is the parameter set that controls the shape of the bell. Parameters a_i, b_i and c_i are referred to as *antecedent parameters*. Figure 3 depicts an example membership function modelled after the set S of "UV exposure". With this function, the UV exposure in Standard Erythema Dose (SED), a standardized measure of erythemogenic UV radiation, of a worker is divided into three fuzzy sets, represented by "Low", "Medium" and "High", based on the worker's skin type. For example, exposure of 4 SED has an $\mu_{Low} = 0.073$, $\mu_{Medium} = 0.811$ and $\mu_{High} = 0.272$ for Skin types V, II respectively
- Layer 2: For rules with multiple preconditions, the layer 2 circle nodes calculate their intersection based on equation (4). The result is forwarded to the next layer.
- Layer 3: The circle nodes of this layer utilize the fuzziness reduction method of equation (5) to combine multiple rules with an identical consequent
- Layer 4: The square nodes in layer 4 compute the level of confidence a of each rule R_i proportionally to the mean degree of membership μ_P of that rule and that rule's weight w_{R_i}, using equation (2). The level of confidence a is referred to as *consequent parameter*
- Layer 5: The circle node in the last layer receives the level of confidence of each combined rule $a_1, \ldots, a_n$ as an input and returns the rule with the highest confidence level $a = \max(a_1, \ldots, a_n)$ as an output of the adaptive network

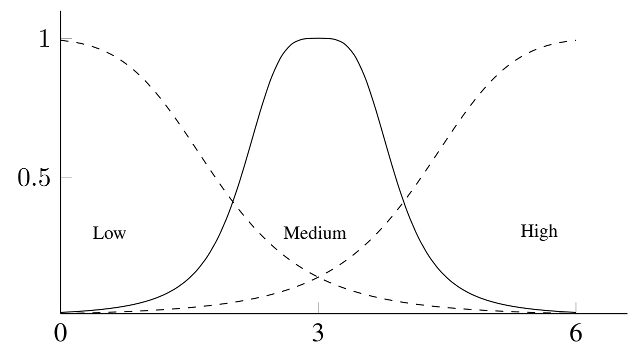


Fig. 3. Membership function for "UV exposure"

V. Experimental Methodology

The ability of UV radiation to induce an acute cutaneous inflammatory reaction of the skin, also refered to as solar erythema, is strongly dependent on its wavelength. The term *Standard Erythema Dose* is used to refer to erythemal effective radiant exposures [21]. One SED is equivalent to an erythemal effective radiant exposure of $100Jm^{-2}$ [22]. An exposure of about 3 SED can produce just minimal erythema in the unacclimatized white skin of the most common northern European skin types. An exposure of $5-8$ SED will result in moderate sunburn while 10 SED or more can result in a painful, blistering sunburn [23].

According to [24], the exposure time t_E in minutes required to induce solar erythema (acute cutaneous inflammatory reaction of the skin to UV radiation) on an individual can be calculated by:

$$t_E = \frac{4000}{60} \times \frac{MEDF \times SPF}{UVI} \tag{7}$$

where $MEDF$ refers to the skin type of the individual, as described in [25] and listed in Table I, SPF is the sun protection factor of any sunscreen applied to exposed skin while UVI is a measure of the level of [sunburning] UV radiation.

Skin type	Description	Scale
I	Celtic	$2-3$
II	Pale	$2.5-3$
III	Caucasian	$3-5$
IV	Mediterranean	$4.5-6$
V	S. American	$6-20$
VI	Negroid	$6-20$

TABLE I
Skin type classification based on the Fitzpatrick scale

Additional factors that affect the UV exposure of an individual also include [26]:

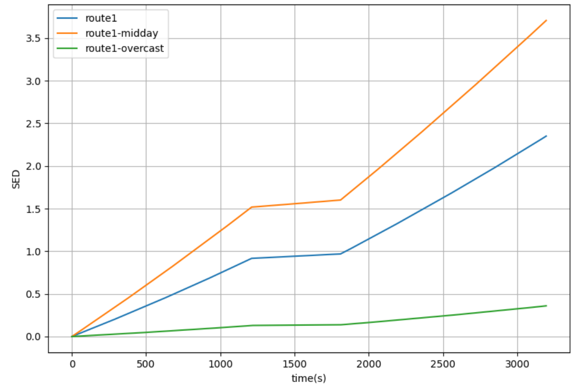
- Solar elevation. UV levels vary with the solar zenith angle, the angle between the sun's rays and the vertical direction. The altitude of the sun depends on the time of year and time of day, as well as on the local Longitude and Latitude
- Altitude. UV levels increase by approximately 10% for every $1000m$ in altitude. As measured in Switzerland and Austria [27], the increase is approximately 8% per $1000m$ of total irradiance, 9% per $1000m$ of UVA irradiance and 18% per $1000m$ for erythemal effective irradiance during the summer
- Clouds. UV radiation is only weakly absorbed by the aerosol particles in the clouds but at the same time can be attenuated by scattering. The impact of an overcast cloud layer is highly variable due to the variability of the optical properties and geometry of the cloud. An annual reduction in UV levels is reported in [21] of approximately $25-33\%$ when clouds are present as opposed to clear skies. A reduction of UV-Biometer intensities is mentioned in [28] to 30% of the clear-sky value at 30^o solar zenith angle, 37% at 40^o, and 41% at 70^o
- Atmospheric attenuation. Thw UV radiation is absorbed by the ozone layer in the stratosphere and scattered by other molecules such as N_2 and O_2
- Surface reflections. Reflective surfaces, such as snow, water, sand and paint, can increase significantly the surrounding levels of UV radiation

The decisions of the FLD are influenced by the above conditions. The FLD can have three possible outputs per individual:

- "No action" - The individual is exposed in no particular UV radiation-related risk
- "Warning" - The individual is exposed to significant levels of UV radiation, it is suggested to move to a shaded or indoors area
- "Emergency" - The individual is in risk of erythemal effective irradiance, it is strongly recommended to a shaded or indoors area

The decisions are transmitted to that worker's smart device indicating a warning that the UV exposure is starting to build up significantly or that the upper threshold of UV exposure has been reached and thus the participant is strongly urged to seek a shadowed area within the site to avoid the chance of skin damage. The safety and health manager of the site is also notified to ensure that the worker complies with the notification.

For the evaluation of the proposed FLD of this paper, first the measurement and monitoring infrastructure used is detailed. Then, the conditions that influence the decision making process are detailed and the rules that consist the knowledge base of the FLD are described.



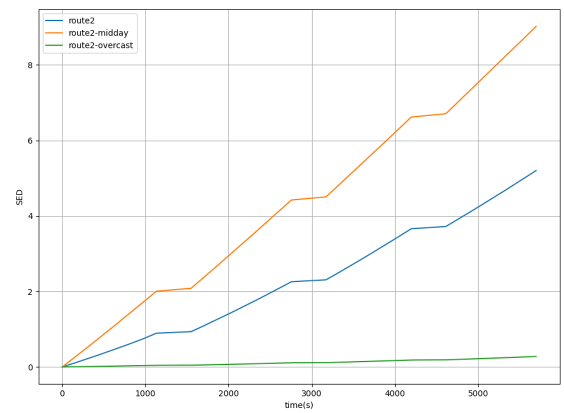


Fig. 4. Experimental Results

Data from geographical locations of volunteers from the CERTH national center for research and technology were collected and used for preliminary measurements. On a later stage of the project, the proposed FLD will be utilized as part of the actual ASSIST-IoT scenario for construction workers. Garmin Fenix 7 smart watches were used to collect data, which were subsequently exported from the implementation of this model in gpx format.

Data for UV index forecasting have been collected using the OpenUV application [29], taking into account the solar zenith angle (SZA) and ozone forecast fields. A representation of the format for data collected is shown in Table II below.

Timestamp	Latitude	Longitude	Elevation	UV
1657726209	40.600221	22.994122	100.800003	0.0388
1657726210	40.600212	22.994122	101.000000	0.0388
1657726214	40.600100	22.994135	102.000000	0.0388

TABLE II
SAMPLE OF COLLECTED DATA FOR UV EXPOSURE

Finally, the time that the workers were in the shade, was also taken into consideration, to ensure that the data were more accurate in terms of the worker's exposure to UV radiation.

VI. Evaluation

The proposed system was able to estimate SED as a function of time. The diagrams in Fig. 4 demonstrate two different routes recorded during the summer, in three different conditions; early morning (just after the sunrise), midday and cloudy-rainy day.

As can be seen from the Fig. 4, in both cases under *overcast* conditions the results are very positive. In contrast, in the first case where the worker was exposed to the sun very early in the morning, after a period of about 1.5 hours harmful dose detected in the case of *route-2* while *route-1* was not long enough to go over the limit. Finally, in the *midday* conditions, the sun became harmful to the workers' health after approximately 50 minutes in both routes.

Utilizing 7, and assuming a Caucasian skin type (the most common for Europeans) and SPF protection of 30, in the *midday* cases, the time required to induce solar erythema would be 24 and 17 minutes for the two routes. In the *overcast* cases, the respective times are 247 and 555 minutes, demonstrating the effect of the weather. Considering *route-1-midday* scenario, if the worker uses higher protection (e.g., SPF 50 or 100) the time to solar erythema from 24 minutes increases to 40 and 80 minutes respectively, signifying the importance of proper sun protection when working outside.

VII. Conclusions and Future work

This paper presented an initial implementation and evaluation of a fuzzy knowledge-based system for estimating the UV exposure for workers in constructions sites. The proposed system can be proven a useful tool to avoid erythema and more serious skin damages. An initial evaluation of the FLD presented in this paper was performed with data captured from volunteers at the CERTH national center for research and technology. Additional experiments will be performed during the pilot demonstrations of the ASSIST-IoT H2020 project.

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