Empirical model for snow/ground reflectivity prediction

by

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Sustainability

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Conservation and Sustainability

in partial fulfillment of the requirements for the degree of
Master of Applied Science in Sustainable Energy

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Abstract

Ground reflected solar radiation is among the factors having a significant impact on the heating and cooling load calculation, solar collector performance, and building energy use prediction. The presence of snow can increase the reflectivity of the ground, leading to increased solar radiation incident on various surfaces of a building. It is common for building performance simulation users to employ the default values of ground reflectivity which can lead to significant inaccuracies, especially for the period when ground is covered with snow.

The thesis describes the development of an empirical model for predicting snow/ground reflectivity. The new model is derived based on point measurements of global horizontal and reflected solar radiation taken for a fifteen-month period (December 2016 – April 2018), at Carleton University, Ottawa. An algorithm is developed for three periods: ground free of snow, non-melting or snow accumulation, and snow melting. The main predictors of reflectivity were found to be the following: zenith angle, cloud cover, snow age, and the difference between the ambient temperature and a threshold temperature which signals the beginning of daily snow melting.

To evaluate its impact, the model is implemented in the ESP-r source code, a software tool used for building performance simulation. The model is applied to calculate the incoming net solar radiation on the south wall of a building and a 60°-tilted surface, for each of the above-mentioned periods. The predicted values are compared with measured data.

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Nomenclature

a	Correction factors for the angle of incidence of circumsolar radiation
b	Correction factors for the angle of incidence of circumsolar radiation
$E_{solar}^{incoming}$	Global horizontal irradiance measured [W/m ²]
$E_{solar}^{reflected}$	Reflected irradiance measured[W/m ²]
F_1	Circumsolar brightening coefficient
F_2	Horizon brightening coefficient
G_0	Extraterrestrial radiation incident on the surface tangent to the outer surface of the atmosphere [W/m ²]
G_{on}	Extraterrestrial radiation incident on the plane normal to the radiation on the nth day of the year [W/m ²]
G_{sc}	Solar constant [W/m ²]
$I_{\beta b}$	Direct solar radiation incident on the inclined surface
I_b	Direct normal solar radiation
I_{dh}	Diffuse horizontal solar radiation
I_{gh}	Global horizontal solar radiation
k	Number of model parameters
MAE	Mean absolute error
n	Day of the year
N	Number of data points
$RMSE$	Root mean square error
R^2	R squared

S_1	Sensitivity of the upper pyranometer [$\frac{\mu V}{W/m^2}$]
S_2	Sensitivity of the lower pyranometer [$\frac{\mu V}{W/m^2}$]
SA	Snow age [hours]
ST	Sky transmissivity
T_a	Ambient temperature [$^{\circ}C$]
$T_{threshold}$	Threshold temperature [$^{\circ}C$]
U_{emf}^1	Output voltage of the upper pyranometer [μV]
U_{emf}^2	Output voltage of the lower pyranometer [μV]
x_k	Predictors
y	Observed response variable (reflectivity)
$\hat{y}_i$	Predicted response variable (reflectivity)
$\bar{y}_i$	Average response variable (reflectivity)

Greek letters

α_s	Solar altitude angle [deg]
β	Slope of the surface [deg]
β_k	Regression coefficients
δ	Current declination of sun [deg]
ε	Random error
θ_i	Angle of incidence of the beam radiation on the inclined surface [deg]
θ_z	Solar zenith angle [deg]
ρ	Reflectivity

Φ	Local latitude [deg]
ω	Hour angle [deg]

1 Chapter: Introduction

1.1 Problem statement

According to the Natural Resources Canada report on energy efficiency trends, between 1999-2013, space heating and domestic hot water accounted for 83% of all residential energy use. Population growth, along with increased demand for new houses (with bigger square footage, number of appliances, and cooling requirements) is leading to an increase in overall residential energy use [1]. In recent years, architects and engineers are employing more extensively building energy simulation tools for code compliance or for designing more energy-efficient buildings, striving to better the built environment.

Moreover, the depletion of non-renewable energy resources motivated the research community to find sustainable solutions, such as solar energy for example, which reduce the dependence on fossil fuels and minimize the greenhouses emissions. Over the past decade, the solar power industry, through new technological innovations, is making a significant impact on the energy system worldwide. Various simulation tools are also used to predict the performance of solar technologies or to find the best solutions to integrate them in the design of new buildings.

To decrease the gap between the predicted and actual energy use of a building, or the performance of a solar technology, accurate input information such as weather data, as well

as data about the microclimate around the building, like ground reflectivity for example, is required.

Ground reflected solar radiation is among the factors having a significant impact on predicting the total solar radiation incident on surfaces with different orientations. As Figure 1 (left) illustrates, the fraction of solar radiation reflected by the vegetated or bare ground is around 20%. However, the presence of snow can significantly increase the reflectivity of the ground, the solar radiation reflected in this case being as high as 90% (Figure 1, right). It is common for building performance simulation users to employ the default values of ground reflectivity (0.2 in ESP-r, EnergyPlus and TRNSYS), which can lead to significant inaccuracies, especially for the period when the ground is covered with snow.

Figure 1. Fraction of solar radiation reflected by vegetated ground (left) and snow (right)

According to Petzold, surfaces covered with snow can experience a high day to day variability in reflectivity, which is in sharp contrast to that of a naturally vegetated surface or bare ground [2]. Snow covers the ground for over four months a year in ten of Canada's

major cities. The longest periods of lingering snow, with at least one centimetre of snow cover, are found at cities in Quebec, Ontario and the Prairie Provinces (Saguenay – Quebec, 155 days; Sudbury – Ontario, 136 days; Edmonton – Alberta, 133 days; Winnipeg – Manitoba, 128 days; and Regina – Saskatchewan, 125 days) [3]. Under such conditions, accurate estimation of snow/ground reflectivity is required in order to make reliable predictions for various applications, such as: heating/cooling load calculation, energy use estimation or solar technology efficiency.

Direct surface measurements of snow reflectivity are rarely available and might contain large errors if the instrumentation is not properly monitored and maintained [4]. Empirical models predicting snow reflectivity can be incorporated in building performance simulation tools, improving the heating and cooling load calculation, as well as the prediction of energy use or solar collectors' performance.

Population growth, along with the increased demand for new houses (with bigger square footage, number of appliances, and cooling requirements) is leading to an increase in overall residential energy use [5]. For Canadian climate, decreasing the heating load and the energy demand for domestic hot water (DHW) can have a significant contribution to the reduction of energy use. Solar radiation is an important renewable energy source, and ground reflectivity is important for the estimation of the energy reaching various surfaces of a building. Modest levels of passive solar design, as site selection and building orientation, also called sun-tempering, can reduce building auxiliary heating requirements from 5% to 25%. Passive solar houses, incorporating more advance features, as proper orientation of windows and window-to-wall ratio optimisation, as well as thermal mass can reduce heating energy use by 25% to 75% compared to a typical structure while remaining

cost-effective on a life-cycle basis [6], leading this way to a more sustainable built environment. Simulating a passive solar house, for half a dozen locations in Canada, Thevehard and Haddad [7] observed a reduction in the sensible heating load over the year between 3.2 and 10.1% on a yearly basis, and as high as 23% on a monthly basis when using algorithms for predicting snow reflectivity (the simple and advanced models presented further in Table 1).

1.2 Research objectives

As was previously said, ground reflected solar radiation is among the factors having a significant impact on the heating and cooling load calculation, as well as on the prediction of energy use or solar collectors' performance. Models predicting the reflectivity have not been investigated in the context of building performance simulation recently.

The research aims mainly to develop an empirical model for predicting snow/ground reflectivity, which can be used to estimate the total solar radiation received by surfaces of various orientation. The model is based on point measurements of global horizontal and reflected solar radiation taken between December 2016 and April 2018, and the reflectivity is predicted for both seasons: ground free of snow and ground covered with snow. An algorithm is developed for three periods: ground free of snow (covered with short grass), non-melting or snow accumulation, and melting, respectively, for the ground covered with snow season. The algorithm is designed to predict reflectivity using metrics which can be calculated by the various simulation tools based on the input information provided by user in weather files.

To quantify its impact, the model is implemented in the ESP-r source code, a building simulation tool frequently used in the academic and research community. The model is

applied to calculate the solar radiation incident on a vertical south oriented surface, very important in passive solar design, and on a 60°-tilted surface. To assess the bias of the model, the predicted values were compared with measured data.

1.3 Literature review

1.3.1 Factors affecting ground/snow reflectivity

Ground reflectivity or albedo is defined as the ratio of reflected to incident solar radiation. Reflectivity is the term used mostly in engineering studies such as building performance simulation and urban heat island effect, while albedo is the term specific to astronomy, remote sensing and climate studies [8]. However, for the present research, only the term reflectivity will be used.

According to the literature, reflectivity depends, in general, on factors such as: the nature of the surface considered, solar altitude/elevation - defined as the angle between the sun and the horizontal or solar zenith angle - defined as the angle between the sun and the zenith line, and cloud cover. Figure 2 illustrates some of the factors affecting reflectivity.

Figure 2. Factors affecting surface reflectivity

For snow covered surfaces, additional factors such as: snow age, accumulated depth, deposition of light absorbing particles (dust and soot), and ambient temperature, should also be considered [9].

Many studies conducted so far show that ground reflectivity increases significantly in the presence of snow. The characteristic values of fresh snow reflectivity reported in literature are between 0.75 [9] and 0.95 [10]. In time, snow reflectivity decreases to values between 0.7 and 0.5 or less [10]. Several studies show that the main factors influencing snow reflectivity are the following: surface grain size (melting leads to snow grains coalescence, decreasing the surface reflectivity), wetness, impurity content (deposition of light-absorbing particles as dust and soot), surface roughness, and the spectral composition and direction of the radiation [11].

Another factor influencing snow reflectivity is the specular reflection. Specular reflection is the result of a defined beam reflected off a smooth surface. According to Duffie and Beckman, for most ordinary surfaces, as bare soil and plant covered soil, ground reflectivity is almost entirely diffuse [12]. Specularity can increase the reflected radiation either forward or backward. Dirmhirn and Eaton [13] found that the reflectivity of fresh fallen snow is almost isotropic, while the specular component increases with the age of snow, and with the number of melting and refreezing processes towards the end of the cold season. They also observed that the forward scattering is strongly increasing with decreasing solar incidence angle, while the back scattering is very small, with no significant variation. A model accounting for specularity was developed by Gueymard [14], in 1987. Nevertheless, the ground reflected radiation calculated with his model was very close to the value provided by the isotropic case. Specularity can be treated in a more complex way

but Thevenard and Haddad [7] consider that the additional computational expense does not seem justified in the case of building performance simulation.

Research has been conducted over time in order to investigate the relationship between the reflectivity of various surfaces and the solar zenith angle, under different sky conditions. The dependence of ground reflectivity on the period of day (before noon and afternoon) was also investigated. Graham and King [15] showed that surface reflectivity increases significantly at solar zenith angles higher than 80 degrees, displaying an asymmetrical diurnal distribution around noon. Reflectivity was slightly smaller under overcast conditions. According to a study conducted by Stanhill et al. [16], the reflectivity measured for any of the investigated surfaces increased significantly with increasing solar zenith angle, and the fraction of cloud cover had no significant influence. Nkendirim [17], in a study conducted in 1972, reported that the dependence of reflectivity on solar zenith angle is more significant in days with clear sky, and almost insignificant on overcast days.

In 1975, when the interest in solar heating was extended to the northerly latitudes, Hunn and Calafell [18] presented a method to estimate snow reflectivity from photographs of twelve representative landscapes, chosen as typical for ground reflective conditions that might be encountered by a solar collector. According to their conclusion, an average ground reflectivity of 0.6 – 0.7 is accurate for most rural landscapes in winter, when snow cover is predominant.

1.3.2 Some ground/snow reflectivity models referenced in literature

Starting in early 1960s, ground/snow reflectivity models were developed under a wide range of snow and atmospheric conditions, for various purposes. Depending on their application (earth's heat balance, climatological models, urban heat island effect,

performance of solar collector or building energy simulation) the model development requires input parameters such as: solar zenith angle, snow depth, snow age/rate of decay, concentration of light-absorbing particles, cloud cover index, and temperature [4].

1.3.3 Influence of solar zenith angle

The relationship between reflectivity and solar zenith angle for various surfaces was investigated for the first time by Nkendirim [17]. The reflectivity of each investigated surface showed a strong exponential relationship with the solar zenith angle (correlation coefficient $r > 0.9$). The dependence of reflectivity on solar zenith angle was noticed to be more significant in days with clear sky, and almost insignificant on overcast days. Arnfield [19], using the model developed by Nkendirim, made further investigations, in order to estimate the potential magnitude of reflectivity variation by season and latitude, for three surfaces (bare soil, short grass and corn) in southern Ontario. The data for each surface, analyzed by diurnal period, as well as by cloud cover, revealed that the dependence of reflectivity on the solar zenith angle is determined by surface roughness.

1.3.4 Influence of snow depth

Snow depth is important because solar radiation can penetrate thin layers of snow. The penetration depth ranges from a few centimeters to as much as 1 m, depending on snow density. Baker et al. [10] analyzed the mean daily reflectivity of snow cover over sod, alfalfa, and bare soil over the course of 19 winters. It was found that reflectivity was increasing with snow depth until around 70%. Taking the value of reflectivity 70% as reference, the required snow depth to effectively mask the underlying surface was 5 cm for bare soil, 7.5 cm for sod, and 15 cm for alfalfa.

The first model taking into consideration the snow depth was developed by Liu and Jordan [20]. The model was assuming a value of 0.2 for all months during which the ground is free of snow. For the period from November to April, when snow covers the ground part of the time, the average reflectivity of the ground for each month was found using the fractional time during the month when snow has a thickness greater than 5 cm, determined from weather records. Reworking the model of Liu and Jordan, Thevenard and Haddad [7] developed a new model, based on the use of monthly snow cover, intended to be used mostly with “typical” weather years.

1.3.5 Influence of snow age/decay

According to Thevenard and Haddad [7], when historical records of snow depth are available, a more complex model can be used. For the first step, the reflectivity is set to a value based on the number of days with snow in a specific month or depending on the type of environment. If snow depth increases from the previous time step, the reflectivity is reset to a high value. The recommended values for reflectivity of fresh snow are (0.75 – 0.85). If the snow depth is not increasing, the snow reflectivity is reduced with each passing day. According to Baker et al., the decay rate was established at 1% per day for the colder months of winter, and between 2.4% and 3.3% for the shoulder months [10]. The higher decay rate can be attributed mostly to the increase in pollutants concentration at the surface of snow (increased absorptivity). A simple energy balance at the surface of the snow is used to determine the melting point. Snow melt is indicated by a snow temperature greater than 0°C, and for this case the decay of snow reflectivity is set to 3% per day [7].

Gray and Landine [21] developed a model for simulating the decrease in reflectivity of melting prairie snow cover. Examining the snow reflectivity for a period from February 1

to the disappearance of seasonal snow, three periods were associated with major changes in the average rate of decrease:

- *Premelt*, the period from February 1 to the start of active melt. During this period, due to metamorphic processes, the reflectivity tends to decrease at a relative slow constant rate. The measured rates of depletion were in the range on 0.004-0.009/day, with an average of 0.006/day.
- *Melt*, when factors such as: changes to the optical properties of the snow cover, the effects of radiation penetrating the ground surface, the development of patchy snow cover, accelerate the decrease in reflectivity. The examination of the reflectivity-depletion curves for 12 continuous melt events showed that the reflectivity at any time $\rho(t)$ could be approximated by the expression $\rho(t) = \rho_i - 0.071 * t$, in which ρ_i is the reflectivity of the snow cover at the start of melt and t is the number of days following the start of continuous depletion.
- *Postmelt*, after the disappearance of the seasonal snow cover. Observations showed that for this period, the reflectivity of the surface remains relatively constant at a value of 0.17, if new snow is not occurring. If new snow is occurring, it was found that it melts more rapidly than the seasonal snow, the decrease being approximated by the expression $\rho(t) = \rho_i - 0.196 * t$.

Kondo and Yamazaki [22] also developed a model of snowmelt based on the heat balance of the snow surface and the energy conservation on the entire snow cover, assuming a linear temperature profile in the snow. For this model, snow reflectivity is assumed to decrease exponentially with time (days) that has passed since the last snowfall.

Another model based on snow decay was developed by Petzold [2]. According to his

observations, most of the time, a small compaction occurs after a snowfall, due to the destruction of fine snowflakes. The snow surface changes also due to accumulation of dust particle from the atmosphere and fine, wind-blown debris from surrounding vegetation. When snowpack melts, there is also a physical change from powder to granular snow due to surface melting. Decay functions were used to obtain the daily change in reflectivity as a function of snow age. Based on his observations, Petzold noticed that in order to completely eliminate the influence of the underlying old snow surface, the new snow cover should have at least one-centimeter depth.

1.3.6 Influence of cloud cover

Petzold [2] conducted a study analyzing the relation between reflectivity and cloud cover for four polar stations, and similar variations were observed at all four stations. Due to significant influence the snow properties have on reflectivity, it was not possible to derive a relationship for an absolute value of reflectivity. However, using a regression analysis, Petzold related an average percent change in reflectivity to the cloud cover amount.

Using sky transmissivity, defined as the ratio between the global radiation incident on a horizontal surface and the extraterrestrial radiation incident on a horizontal plane, as an index of cloudiness, Nkendirim [17] investigated the relationship between the reflectivity and solar zenith angle for three ranges of transmissivity: less than 0.25, 0.25–0.5, and greater than 0.5.

These values of transmissivity corresponded approximately to overcast sky, intermittent cloudiness and clear sky, respectively. Nkendirim observed that for the same value of solar zenith angle, the reflectivity increases with increasing sky transmissivity. The dependence of the reflectivity on solar zenith angle was most noticeable for clear sky,

while for overcast sky the dependence was insignificant.

1.3.7 Influence of solar radiation

A study investigating the progress of snow reflectivity was conducted at a research site in Norway, for the winter of 1991 [23]. It was found that as long as the snow depth is large enough to prevent absorption of solar radiation by the underlying terrain, the reduction of reflectivity over time decreases as the snow undergoes a process of metamorphosis. As the snow depth becomes less than approximately 10 cm and the area of bare ground patches grows, it was noticed an increase in the temporal rate of reduction in reflectivity.

An accumulated daily maximum temperature index was found to be a good predictor of both the long-term development of the snow reflectivity and the daily mean reflectivity. The accumulated daily maximum temperature index is expressed as the summation of the maximum temperature over freezing point recorded for every day since the last snow fall. Analyzing the difference between the observed and predicted long-term reflectivity, it was noticed that it is correlated with the incoming solar radiation. It was found that the incoming solar radiation and snow reflectivity are negatively correlated, meaning that reflectivity decreases with increasing incoming solar radiation. Linear regression was performed for a winter period with no melting and for two distinct melting periods. First, snow reflectivity was determined as a function of temperature index alone. An increase in accuracy of 2-6% was noticed when solar radiation was included in snow reflectivity prediction [23].

1.3.8 Reflectivity models referenced in literature

Table 1 presents some of the reflectivity models referenced in literature, and the required inputs.

Table 1. Relevant snow/ground reflectivity models found in literature

Reflectivity Model	Input Data	Reference
The Thevenard and Haddad simple model		
$\rho_{g,i} = \rho_{nosnow} \cdot \left(1 - \frac{N_{snow,i}}{N_i}\right) + \rho_{snow} \cdot \frac{N_{snow,i}}{N_i}$ <p>where: ρ_{nosnow} – snow-free reflectivity of ground ρ_{snow} – snow reflectivity $N_{snow,i}$ – average number of day with snow in month i N_i – number of days in month i</p>	<ul style="list-style-type: none"> • ρ_{nosnow} – snow-free reflectivity of ground • ρ_{snow} – snow reflectivity • $N_{snow,i}$ – average number of day with snow in month i • N_i – number of days in month i 	Thevenard and Haddad [7] follows Liu and Jordan [20]
The Thevenard and Haddad advanced model		
<ul style="list-style-type: none"> • Assumes real historical record of snow depth is available; • If snow depth increases from the previous time step, reflectivity is set to a high value; • Reflectivity is then reduced with each passing day; • Snow melt is determined applying a simple energy balance at the surface of snow. <p>When snow is less than 5 cm, the following formula is applied:</p> $\rho_g = \rho_{g,nosnow} \cdot \left(1 - \frac{d}{d_0}\right) + \rho_{snow} \cdot \frac{d}{d_0}$ <p>where: d – snow depth d_0 – snow depth 5 cm ρ_{snow} – reflectivity calculated for snow depth greater than 5 cm $\rho_{g,nosnow}$ – month dependent reflectivity</p>	<ul style="list-style-type: none"> • d – snow depth • d_0 – snow depth 5 cm • $\rho_{g,nosnow}$ – month dependent reflectivity • ρ_{snow} – snow reflectivity 	Thevenard and Haddad [7]
Other models for winter		
$\rho = 0.839 - 0.0473 \cdot n^{1/2}$ <p>where: n – number of days after snowfall</p>	<ul style="list-style-type: none"> • Number of days after snowfall 	Baker et al. [10]
$\rho = \rho_{min} + (\rho(0) - \rho_{min}) \cdot e^{-\frac{n}{K}}$ <p>where: ρ_0 – reflectivity of snowfall day (0.85) ρ_{min} – converged reflectivity value n – number of days after snowfall K – rate of decrease parameter</p>	<ul style="list-style-type: none"> • Number of days after snowfall 	Kondo and Yamazaki [22]
$\rho = \rho_{t-1} - DR$ <p>where: ρ_{t-1} – reflectivity from preceding day DR – decay rate</p>	<ul style="list-style-type: none"> • Maximum temperature • Net solar radiation • Snow depth • Starting reflectivity 	Gray and Landine [21]
<p>For melting season:</p> $\rho = 0.90 - 9.21 \times 10^{-4} \cdot T_{acc} - 0.0042 \cdot SR$ <p>where: T_{acc} – accumulated daily maximum temperature index (°F) SR – solar radiation (mW/cm²)</p>	<ul style="list-style-type: none"> • Temperature • Solar radiation 	Winther [23]
Model for vegetated ground		
<p>For vegetated ground:</p> $\rho = \rho_0 \cdot e^{bz}$ <p>where: ρ_0 – statistical estimate coefficient z – solar zenith angle (degree) b – coefficient describing the rate of reflectivity changing</p>	<ul style="list-style-type: none"> • Solar zenith angle • Surface properties 	Arnfield [19]

1.4 Thesis Outline

The thesis, excluding Chapter 1, is organized as follows:

- **Chapter 2: Preliminary variable selection, experiment design and methodology** provides the criteria for the preliminary variables selection, the description/selection of the site where the field study was conducted, as well as the description of the instruments used for measuring and recording data, and the procedure followed for calculating the measurement error.
- **Chapter 3: Data validation, exploratory data analysis and observations** describes the procedure applied for validating the observed data and for conducting the exploratory statistical analysis. The general observations made based on the statistical analysis, the preliminary multiple linear regression and hypothesis testing performed on a first set of data are also presented.
- **Chapter 4: Functional form of the model** presents the methodology followed for finding an equation that best describes the relationship between variables, and a short description of the functional form for each of the three periods of interest.
- **Chapter 5: Testing the model fit and error analysis** describes the statistical analysis performed to assess the goodness of fit of the model. Descriptive statistics of residuals and their distribution are also presented.
- **Chapter 6: Model validation** describes the methodology applied for validating the model.
- **Chapter 7: Building performance simulation in ESP-r and model implementation** presents a short description of ESP-r, the treatment of solar radiation incident on external surfaces, and the energy balance applied at the

external surface of a wall. A short description of weather files for building performance simulations and the implementation of the model in the ESP-r source code are also presented.

- **Chapter 8: Impact of the model on estimation of solar irradiance incident on various surfaces** provides a short description of the simplified model of Urbandale Centre used for simulation, the estimation of the solar irradiance incident of the south wall, the estimation of the solar irradiance incident on a 60° tilted surface, and the analysis of results.
- **Chapter 9: Conclusions and recommendations for future work** presents some of the conclusions derived after the completion of the research, and a few recommendations for future work.

2 Chapter: Preliminary variables selection, experiment design and methodology

2.1 Preliminary variables selection

As the literature review presented in Chapter 1 illustrates, research investigating snow/ground reflectivity was conducted starting in early 1960s. Various models were developed under a wide range of snow and atmospheric conditions, for applications such as: earth's heat balance, climatological/hydrological models, urban heat island effect, performance of solar collectors, building energy simulation. Among the required input parameters of these models can be encountered: solar zenith angle, snow depth, snow age/rate of decay, snow grain size, concentration of light-absorbing particles, spectral composition of solar radiation, cloud cover index, and temperature [4].

Currently, in the building performance simulation field, there are two models used for predicting reflectivity, both for the period when ground is covered by snow: a “simple” and an “advanced” one, developed by Thevenard and Haddad [7] in 2006 (see Table 1). The simple model predicts the reflectivity based on the number of days with snow in a month, while the complex one based on the rate of snow decay and the value of reflectivity for fresh snow.

The present study investigates the variation of reflectivity for both seasons: ground free

of snow, as well as ground covered with snow. For the ground covered with snow season, two periods were investigated: snow accumulation and snow melting, respectively. The objective was to develop an empirical model for predicting reflectivity based on parameters easy to calculate/measure, and which are familiar to professionals from the building performance simulation or solar engineering field. The model should provide sufficiently accurate results, without the use of complex algorithms or significant increase of the simulation run-time. Since solar zenith angle and cloud cover are parameters with significant impact on the solar radiation reaching the ground, the quantitative influence they have on ground reflectivity was investigated. For the winter season, when snow covers the ground, a third variable, snow age is added to the model for the snow accumulation period. For the snow melting period, a new variable, the difference between the ambient temperature and a threshold temperature signaling the start of snow melting, is also added.

Typically, the information regarding snow fall events and/or snow depth is either missing from the weather files used for simulation or is not easy to find/very accurate for the meteorological station closest to the site of interest. As such, instead of using an additional file containing daily/hourly snow age, like the snow depth file required by the “complex model” developed by Thevenard and Haddad, the new model will detect the presence of snow employing climatic information commonly available in the weather files, such as: dry and wet bulb temperature, atmospheric pressure, relative humidity, and global horizontal solar radiation.

A detailed description of each variable employed by the model will be presented in Section 2.3.

2.2 Site selection/description

The field study was conducted at Urbandale Centre for Home Energy Research (CHEeR), Carleton University, Ottawa, ON (45.38°N, 75.69°W). The Urbandale Centre is located on the north-east area of Carleton University campus, in a semi-open environment, characteristic for many suburban or rural developments, with the surrounding ground covered with short grass.

CHEeR is designed as a research-intensive facility for sustainable, energy efficient housing. Most projects at CHEeR are specialized in investigating new solar technologies and alternative cooling methods.

Figure 3. Urbandale Centre for Home Energy Research (south view)

Modelling and predicting the performance of the new systems is also a significant component of the research. Weather data and information about the environment are

important input data for simulation and modelling. Various weather devices are mounted on the roof/facade of CHEeR, for monitoring parameters such as dry bulb temperature, wind speed, global horizontal solar radiation or solar radiation incident on surfaces of various orientations.

2.3 Instruments used for measuring and recording data

The sensor used for measuring the global horizontal and reflected solar radiation was a Kipp and Zonen CMA6 albedometer, which is sensitive to wavelengths of about 0.3 to 3.0 μm . The albedometer comprises two CMP6 sensing elements and dome assemblies in a single housing, with two signal outputs on one signal connector. Each CMP6 element features a 64-junction thermopile sensing element with a highly absorptive and spectrally flat black coating to capture incoming radiation. The absorbed solar radiation causes a temperature gradient across the calibrating sensing element that generates an electromotive force (emf) in the thermopile. They are protected by two high-quality concentric domes, 2 mm thick, and the housing is completely sealed. The two concentric domes reduce directional error and improve thermal isolation. Figure 4 presented further illustrates a schematic representation of the albedometer, as well as the other existing devices mounted on Urbandale Centre roof and south wall.

As Figure 4 shows, the upper sensor of the albedometer measures incoming global solar radiation and the lower one measures the solar radiation reflected from the surface below. When the two signal outputs are converted to irradiance, in W/m^2 , the reflectivity can be simply calculated, dividing the reflected radiation to the incoming one [24].

Figure 4. Schematic representation of the albedometer
(adapted with permission from Curtis Meister)

The albedometer was mounted horizontally, as Figure 4 illustrates, and it was kept at 1.5 m height above the ground/snow surface, to promote spatial averaging. Efforts were made to minimize the shading from the device and mounting equipment, at low solar elevation, by rotation of the instrument. The solid angle of the CHEeR house from the perspective of the upper pyranometer was found to be 0.34 sr (approximately 5% of the total hemispherical view of the pyranometer), while solid angle of the CHEeR house from the perspective of the down facing pyranometer was found to be 0.11 sr (approximately 1% of the total hemispherical view of the pyranometer). Taking into account the small values of the two solid angles, and the fact that reflectivity represents the ratio between the measurement of the down facing pyranometer and the measurement of the up facing one,

the influence of the proximity of the CHEeR house was negligible.

For the period December 10, 2016 - July 20, 2017, the global horizontal and reflected solar radiation were sampled every second and averaged at five seconds time-interval using a National Instruments cFP 2220 data logger. For the period July 21, 2017- April 7, 2018, the global horizontal and reflected solar radiation were sampled every 10 second using a National Instruments PXIe 1078 data logger.

2.4 Variables measurement/calculation

2.4.1 Global horizontal and reflected solar radiation

Ground reflectivity is defined as the ratio of reflected to incident solar radiation [7] and it cannot be measured directly. Reflectivity is derived from measurements of reflected and global horizontal solar radiation, respectively.

The reflected and global horizontal solar radiation were measured using a Kipp and Zonen CMA6 albedometer, as was described in Section 2.3, most of the time during the daylight hours. A LabView virtual instrument was used to convert the two signal outputs of the albedometer to irradiance, employing the following relationship:

$$E_{solar}^{incoming} = \frac{U_{emf}^1}{S_1} \quad (1a)$$

$$E_{solar}^{reflected} = \frac{U_{emf}^2}{S_2} \quad (2b)$$

where $E_{solar}^{incoming}$ is the global horizontal irradiance [W/m^2], U_{emf}^1 is the output voltage of the upper pyranometer [μV], S_1 is the sensitivity of the upper pyranometer [$\frac{\mu V}{W/m^2}$], $E_{solar}^{reflected}$ is the reflected irradiance [W/m^2], U_{emf}^2 is the output voltage of the lower pyranometer [μV], S_2 is the sensitivity of the lower pyranometer [$\frac{\mu V}{W/m^2}$]. The sensitivities

provided by the manufacturer are the following: $S_1 = 18.01 \left[\frac{\mu V}{W/m^2} \right]$, and $S_2 = 17.64 \left[\frac{\mu V}{W/m^2} \right]$.

The values of global horizontal and reflected irradiance were recorded and stored in a database daily. The reflectivity was calculated by dividing the reflected solar irradiance to the global horizontal one.

2.4.2 Solar zenith angle

The solar zenith angle was calculated using the values of solar altitude provided by the United States Naval Observatory (USNO), Sun or Moon Altitude/Azimuth Calculator [25].

The calculator uses the following equation to compute the zenith angle [12]:

$$\cos(\theta_z) = \sin(\alpha_s) = \sin\Phi\sin\delta + \cos\Phi\cos\delta\cos\omega \quad (2)$$

where θ_z is the solar zenith angle [deg], α_s is the solar altitude angle [deg], Φ is the local latitude [deg], δ is the current declination of sun [deg], and ω is the hour angle [deg].

Figure 5 illustrates a schematic representation of the solar zenith and altitude angles.

Figure 5. The solar zenith and altitude angle (adapted from [12])

The declination δ is calculated as a function of the day of the year (n) using the

following equation [12]:

$$\delta = 23.45 \cdot \sin\left(360 \cdot \frac{284 + n}{365}\right) \quad (3)$$

The hour angle ω , represents the angular displacement of the sun east or west of the local meridian due to rotation of the earth on its axis at 15° per hour, morning negative, afternoon positive [12].

The solar zenith angle, in degrees, was calculated subtracting the value of solar altitude from 90°. Daily series of minutely calculated solar zenith angle were also stored in data files.

2.4.3 Cloud cover

As was previously discussed, sky transmissivity was used as an indicative of the cloud cover. Variation of the earth-sun distance leads to variation of the extraterrestrial radiation flux in the range of $\pm 3.3\%$ [26]. For engineering calculations, extraterrestrial radiation incident on the plane normal to the radiation on the n th day of the year (G_{on}), in W/m^2 , is calculated using the following formula [12]:

$$G_{on} = G_{sc} \left[1 + 0.033 \cdot \cos\left(\frac{360 \cdot n}{365}\right) \right] \quad (4)$$

where G_{sc} is the solar constant, defined as the energy from the sun per unit time received on a unit area of surface perpendicular to the direction of propagation of the radiation at mean earth-sun distance outside the atmosphere. A value of 1367 W/m^2 was used for the present study [12].

Extraterrestrial radiation incident on the surface tangent to the outer surface of the atmosphere (G_{θ}), in W/m^2 , is given by the formula [12]:

$$G_0 = G_{on} \cdot \cos(\theta_z) \quad (5)$$

where G_{on} is the extraterrestrial radiation incident on the plane normal to the radiation [W/m^2] and θ_z is the solar zenith angle [deg].

Finally, the sky transmissivity (ST) for every minute, was found as the ratio between the measured global radiation incident on a horizontal surface, and the calculated extraterrestrial solar radiation on a horizontal plane, G_o . Figure 6 illustrates the factors having impact on sky transmissivity for clear and overcast sky.

Figure 6. Sky transmissivity for clear and overcast sky (adapted from [26])

According to Carroll [26], typical values for sky transmissivity are between 50% and 80% for clear sky, and between 0% and 50% for mixed and overcast sky.

2.4.4 Snow age/properties

In addition to measurement of global horizontal and reflected solar radiation, a daily “weather log” was kept in order to record information such as: snow fall events, snow properties/conditions, snow depth and age, as well as cloudiness.

For example, in the case of a snow fall event, information such as: starting and ending time, intensity (qualitative observations such as heavy, moderate and light snow), snow properties (small/large flakes, dry/wet) were recorded in the weather log. In order to measure the snow depth, the guidelines provided by the U.S. National Weather Services were followed. According to these, snow depth is the total depth of snow (including any ice) on the ground at the normal observation time. The snow depth includes new snow that has fallen combined with snow already on the ground [27]. As Figure 7 illustrates, a measuring tape having numbers easy to read and marked in measures of tenths of a centimeter was used to perform the measurement.

Figure 7. Snow depth measurement

According to the previously mentioned guidelines, the snow depth should be measured in locations where the effects of blowing and drifting are minimized, immediately after the end of the snowfall. It was not always possible to measure the snow depth right after the end of a snowfall event, and as such, it was decided to record the snow depth every morning, before starting the measurement of reflected and global horizontal solar radiation.

The measurement was performed at a fix point, close to the mounting post of the albedometer, to be representative for the snow surface seen by the pyranometer measuring the reflected solar radiation. Same convention was applied for the snow age. Every morning the snow age, in hours, was set to a value equal to the number of hours since the end of the last snowfall event.

The determination of cloud cover was performed daily by visual observations. Hourly qualitative assessment such as: clear sky, mixed or intermittent cloudiness, and overcast sky were recorded in the weather log.

Similar observations were made also for the period when the ground was free of snow (rainfall events occurrence and duration, grass properties – freshly cut or not, presence of dew, cloudiness). Appendix A presents samples of daily entries in the weather log, illustrating the information recorded for each period.

2.5 Calculation of measurement error

The main sources of error in snow/ground reflectivity calculation were found to be the following: the albedometer, its mounting equipment, and the measurement and recording of the instrument output. Hamilton and Collingbourne [28] have indicated that pyranometers are causing measurement errors due mainly to the dependence of their output on temperature and on the solar azimuth and solar zenith angles, as well as due to their inherent non-linearity.

According to Kipp and Zonen [24], when performing reflectivity measurements with a CMA6 albedometer, the non-stability error is smaller than 1%, the non-linearity error is also smaller than 1%, the temperature error is smaller than 4%, while the tilt response error

is smaller than 1%. The estimated instrument calibration uncertainty provided by the manufacturer was $\pm 2.57\%$. Calculations using the method outlined by Slatyer and McIlroy [29] were performed to find the shaded area due to the mounting equipment. The shaded area was found to be less than 0.15% of the total area seen by the device, and as such, no adjustment of the reflectivity value was made to correct the influence of the shaded area.

Accurate measurement of the global radiation requires proper levelling of the detector surface. Efforts were made to level the instrument properly, by bringing the bubble of the spirit level centrally within the marked ring. The deposition of impurities or snow on the upright dome could result in the reduction of incoming solar radiation, leading this way to a false increase in reflectivity. As such, the albedometer was periodically cleaned to avoid the introduction of uncharacteristic values in the data set. Two other pyranometers measuring the global horizontal solar radiation are mounted on the roof of the Urbandale Center. The records provided by the CMA6 albedometer used for the study were in close agreement with the ones provided by the other two pyranometers most of the time (significant differences were noticed generally after heavy snowfalls or freezing rain, when for a short period, the devices mounted on the roof were covered with snow or ice).

According to the albedometer mounting instructions, the device should be located at a distance at least ten times bigger than the highest obstacle, such that no shadow will be casted upon device at any time. Nevertheless, the site available for performing the measurements did not meet the above requirement, and for sunny days, at low solar altitude, some of the surrounding trees were casting shadows on the device and the surface below for a short period of time (approximately one hour after sunrise and half an hour before sundown). Moreover, for cold days (temperature lower than $-20\text{ }^{\circ}\text{C}$), due to the

high difference between the ambient temperature and the device temperature (for security reasons, the device was kept inside Urbandale Centre during the night), at least 10-15 minutes were required for the instrument to stabilize. The measurements corresponding to those time intervals were eliminated also from analysis, to avoid the introduction of inaccurate data in the data set used for deriving the model.

For the period December 2016 – July 2017, the incident and reflected solar radiation were measured every second and averaged at five seconds time interval. The averaged values were recorded using a National Instruments cFP 2220 data logger. The error of the data logger was $\pm 5.72\%$. The total bias error of the system albedometer-data logger associated with reflectivity calculation was found to be $\pm 8.40\%$. For the period August 2017 – April 2018, a National Instruments PXIe 1078 data logger was used. The error was only $\pm 3.60\%$ in this case, leading to a total bias error associated with reflectivity calculation of $\pm 5.70\%$.

The solar irradiance incident on a south oriented surface and on a 60° tilted surface was measured using a CMP10 pyranometer. According to Kipp and Zonen, for the CMP10 pyranometer, the non-stability error is smaller than 0.5%, the non-linearity error is smaller than 0.2%, the temperature error is smaller than 1%, while the tilt response error is smaller than 0.5% [24]. The estimated instrument calibration uncertainty provided by the manufacturer was $\pm 1.35\%$. The total measurement uncertainty of the solar irradiance measurement was found to be 3.9%.

The methodology followed to calculate the total bias error was the square root of the sum of squares. Detailed calculations of the measurement uncertainty are presented in Appendix B.

3 Chapter: Data validation, exploratory data analysis and general observations

The exploratory data analysis was performed using the data set collected during the period December 2016 – July 2017, recorded using the National Instruments cFP 2220 data logger.

3.1 Data validation and preparation

Data reduction involves the distillation of raw data into a form that can be subsequently analyzed. It may involve averaging multiple measurements, comparing with physical limits or expected ranges, and rejecting outlying measurements. Data validation or proofing data for consistency is a process for detecting and removing gross or “egregious” errors in the monitored data [30]. The values of global horizontal and reflected irradiance recorded at five seconds time interval were averaged minutely. The independent variables: solar zenith angle, sky transmissivity and snow age were calculated also minutely. The variables were organized in daily matrices, having the following columns: Time; Reflectivity; Solar zenith angle, Sky transmissivity, and Snow age.

The second step in organizing the data was the cleaning process. As was stated in Section 2.5, for sunny days, it was noticed that some of the surrounding trees were casting shadows on the device and the surface below, for approximately one hour after sunrise and around half an hour before sundown. The values corresponding to those time intervals were

excluded from the study, to avoid the introduction of uncharacteristic values in the data set used for deriving the model. During the field study, a few days with heavy wet snow or freezing rain were recorded. Due to the deposition of snow or ice on the device (cleaning the device very often was also disturbing for the data collection process), the global horizontal solar radiation was recording values significantly lower than for days with similar cloud cover conditions. The time series corresponding to those days were also eliminated when creating the data sample. For the remaining data set, a finer check for data quality was performed, by flagging data when they exceed the physically stipulated ranges. Daily scatter plots (reflectivity versus zenith angle, generally) were employed also, for detecting outliers by visual scrutiny. The occurrence of the outliers was investigated in correlation with the information recorded in the weather log. The uncharacteristic values of reflectivity due to incorrectly measured data were eliminated from the analysis.

A sample was constructed for each period of interest: ground free of snow, snow accumulation and snow melting. Analyzing the daily scatter plots was noticed that for the same zenith angle, the values of reflectivity are slightly higher before noon than after noon. In order to construct a representative, unbiased sample only the data sequences corresponding to full days were included.

3.2 Exploratory data analysis

Descriptive summary measures of sample data are meant to characterize salient statistical features of the data for easier reporting, understanding, comparison and evaluation [30]. Using the Data Analysis tool of Microsoft Excel, descriptive statistics were derived for each period of interest (ground free of snow, snow accumulation and snow

melting). Table 2 presents the summary statistics for the three periods previously mentioned.

Table 2. Summary statistics for sample data

Statistics	Ground free of snow	Snow accumulation	Snow melting
Mean	0.204	0.799	0.670
Standard Error of Mean	0.0002	0.0007	0.0021
Median	0.201	0.821	0.688
Mode	0.247	0.950	0.640
Standard Deviation	0.027	0.095	0.141
Sample Variance	0.0007	0.0091	0.0198
Kurtosis	2.075	2.274	-0.335
Skewness	0.630	-0.865	-0.641
Range	0.268	0.576	0.666
Minimum	0.110	0.374	0.252
Maximum	0.378	0.950	0.918
Count	20123	20922	4445

During the exploration of the data, graphs serve generally two purposes, they provide a better means of assimilating broad qualitative trend behavior of the data than can be provided by tabular data, and they provide an excellent manner of communicating to the reader what the author wishes to state or illustrate [30].

Plotting histograms is very useful because they provide insight into the underlying parent distribution of data dispersion and can flag outliers as well. The sample for each period was divided in bins of equally space intervals (0.015 space interval). Appendix C presents the resulting histogram for each period.

After the analysis of both the descriptive statistics and the histograms, it was noticed that the distribution of the data for the ground free of snow is normal or Gaussian. For the snow accumulation period, the values of the skewness and kurtosis, as well as the histogram, indicate that the distribution is skewed to the left. For the snow melting period,

it was noticed that the variance of the data is very high compared with the two previous periods (more than 10 times), and the distribution is not normal.

Scatter plots allows visual determination of the trend line between two variables. For both seasons, ground free of snow and ground covered with snow, the minutely averaged values of reflectivity were plotted versus time/zenith angle to observe the diurnal trends.

Analysing the values of global horizontal radiation and sky transmissivity, as well as the daily records regarding the cloud cover (the weather log), it was noticed that sky transmissivity has values less than 0.3 for overcast sky, between 0.3 and 0.6 for intermittent cloudiness or mixed sky, and higher than 0.6 for clear sky. Figure 8 illustrates the daily variation of reflectivity with the solar zenith angle for three representative types of cloud cover: clear sky, mixed sky or intermittent cloudiness, and overcast sky.

Figure 8. Daily variation of reflectivity with solar zenith angle and cloud cover for representative days

For two of the investigated periods, ground free of snow and snow accumulation, a positive correlation was noticed between reflectivity and solar zenith angle (reflectivity increases with the increase of the solar zenith angle). Moreover, the increase in reflectivity is higher for higher values of the solar zenith angle. For the snow melting period, for most days, in the afternoon, when the snow melting rate is higher, the effect of zenith angle is no longer noticeable. A positive correlation was also noticed between reflectivity and sky transmissivity (for equal solar zenith angles, the reflectivity is higher when the sky transmissivity is higher).

The daily average values were also calculated and plotted versus time for a whole year, in order to observe the seasonal and monthly trends. Figure 9 illustrates the seasonal variation of daily average reflectivity over one year.

Figure 9. Seasonal variation of average daily reflectivity

According to Figure 9, at the beginning of winter, when the snow accumulation season takes place, the reflectivity has a small variation around the mean value of 0.8. Towards the end of the winter, when the snow melting season starts, the variation of reflectivity increases significantly, for some days reflectivity decreasing from 0.85 to 0.35. After the snow melting season, when the ground is free of snow, the variation of reflectivity is also small, around the mean value of 0.2.

3.3 Multiple linear regression and hypothesis testing

In order to find the optimal relation among variables, the method of multiple regression analysis was used. Investigating the daily and seasonal trends of reflectivity, a multiple linear regression analyses was considered suitable for starting the process of finding the functional form of the model. Figure 10 illustrates a linear approximation of the daily and seasonal trend of reflectivity.

Figure 10. Linear approximation of daily and seasonal variation of reflectivity

The analysis was based on a function of the following type:

$$y = \beta_0 + \beta_1 \cdot x_1 + \beta_2 \cdot x_2 + \cdots + \beta_k \cdot x_k + \varepsilon \quad (6)$$

where y is the response variable (snow/ground reflectivity), x_k are the predictors (zenith angle, sky transmissivity and snow age), β_k are the regression coefficients, and ε is a random error, which allows each response to deviate from the average value of y by the amount ε . The following assumptions are made regarding the values of ε : (1) are independent; (2) have a mean of 0 and a common variance σ^2 for any set of $x_1, x_2, \dots, x_k$; and (3) are normally distributed [31]. As was previously described in Chapter 2, the solar zenith angle, sky transmissivity and snow age were assumed to be significant parameters for predicting reflectivity. However, when performing the regression, instead of using the value of the solar zenith angle, a derived value, which approximates better the variation of reflectivity with the zenith angle, $x_1 = 1 - \cos(\theta_z)$ was used. The analysis searches for the combination of predictors x_k (including regression coefficients β_k) resulting in a response y , which minimizes the error ε (least-squares regression line).

In order to determine whether the derived relationship between the response variable and the selected predictors is significant, the null hypothesis test was applied. The null hypothesis (H_0) was formulated as follow: for a specific parameter, x_k , there is no influence on the response variable, y (meaning the coefficient β_k is equal to zero). The p -value is a number between 0 and 1 and it can be interpreted in the following way:

- A p -value smaller than the α -level indicates strong evidence against the null hypothesis, so the null hypothesis is rejected.
- A p -value larger than the α -level indicates weak evidence against the null hypothesis, so it cannot be rejected.

The α -level represents the probability of rejecting the null hypothesis. The typical

values are: 0.1 for 90% confidence interval; 0.05 for 95% confidence interval, and 0.01 for 99% confidence interval [31].

The p-value test was applied for two sets of data: ground free of snow and ground covered with snow. The p-values corresponding to each regressor were calculated for the 95% confidence interval and, as Table 3 illustrates.

Table 3. The multiple regression coefficients and the corresponding p-values

	Ground free of snow		Ground covered with snow	
	Coefficients	p-value	Coefficients	p-value
Intercept	0.175	0	0.900	0
Variable 1: $1 - \cos(\theta_z)$	0.070	3.3×10^{-143}	0.030	2.9×10^{-18}
Variable 2: Sky transmissivity	0.040	0	0.100	0
Variable 3: Snow age	-	-	0.015	5.6×10^{-56}

As Table 3 illustrates, the p-value corresponding to each coefficient was always smaller than 0.05, the value of α -level for 95% confidence interval. This indicates that all three variables: zenith angle, sky transmissivity, and snow age statistically significant parameters.

3.4 General observations

Some of the observations made during the exploratory analysis of data may be summarized as follows:

- The measured snow reflectivity displays a small variance during the winter months (monthly average 0.004). The variance increases 10-fold during the melting season (monthly average 0.038).
- During the accumulation period, the reflectivity is rarely below 0.75 and very often

the values exceed 0.85 due to new snow-fall.

- For fresh snow, and solar zenith angles higher than 80 degrees the reflectivity might have values between 0.9 and 0.95, while for solar zenith angle smaller than 80 degrees the values are most of the time between 0.8 and 0.9.
- According to literature, reflectivity depends on numerous factors such as: particle size, wetness, and impurities accumulation. Visual observation of the snow cover led to the conclusion that fresh powdery looking snow (very frequent during accumulation period) might have average reflectivity as high as 0.9, while fresh snow with a high content of water (frequent during melting period) around 0.8 or lower. Likewise, clean snow, one week old might have average reflectivity around 0.7, while one-week old snow with a high level of particulate matter (dust and soot) accumulation as low as 0.45. Figure 11 presents four photographs illustrating values of reflectivity characteristic for snow of various depth and age.

Fresh snow, less than 5 cm, Reflectivity < 0.6

Fresh snow, more than 5 cm, Reflectivity > 0.8

Frozen, icy snow, Reflectivity ~ 0.6

Snow with high content of impurities
Reflectivity ~ 0.45

Figure 11. Reflectivity values of snow of different depth and age

The photographs presented in Figure 11 were taken during the data collection period, and the reflectivity was measured and recorded at the time the photos were taken.

- At the end of the active melting of snow, the reflectivity has the average value of 0.17 and it can reach values as low as 0.07 (typical value for water), depending upon the presence of a continuous film of water at the ground surface.
- The variation of snow reflectivity increases with the solar zenith angle. According to the daily variation of reflectivity, presented in Figure 9, on days with clear sky the influence of the solar zenith angle on reflectivity is more noticeable than on days with overcast sky. Moreover, for days with clear sky, it can be noticed that the variation is higher in the morning (the zenith angle has higher values) than close to noon (the zenith angle is smaller than in the morning). According to literature [17], the lower values of reflectivity noticed on overcast days is a consequence of the sky being the effective radiator instead of the sun.
- For similar solar zenith angles, the values of reflectivity before noon are slightly higher than the afternoon ones. According to literature [2], [4], [13] investigations indicate that reflectivity for the infrared and near-infrared part of the spectrum are markedly lower than for visible light, hence the difference in spectral composition of radiation from morning to afternoon. The state of vegetation (weltering in the afternoon) or snow surface (more particulate matter accumulation) may partly account for this phenomenon also.
- The reflectivity and snow age are negatively correlated (reflectivity decreases while the snow age increases). The decreasing rate of reflectivity due to snow age was

found to have an average daily value of 2.2% for the accumulation period and 17.1% for the melting period.

The first multiple linear regression was performed on the set of data collected between December 2016 and July 2017. For the winter period, the resulting functional form failed to capture the high decay rate of the reflectivity due to rapid snow melting towards the end of the period. To improve the accuracy of the model it was decided to divide the data into two periods:

- Non-melting or accumulation period – snow melting rate very small, frequent snow falls, and ambient temperature mostly below 0°C;
- Melting period – snow melting rate high, isolated snow falls, and ambient temperature frequently above 0°C.

Analysing the seasonal variation of reflectivity, presented in Figure 9, it can be observed that for the winter season, a substantial change in trend occurs near day 50 (February 20). Starting from this date, the decrease of reflectivity was significantly higher compared with December and January. Based upon observation of ambient temperature and the rapid decrease of snow depth and reflectivity, February 21 was considered to be the beginning of the melting period. As Figure 9 shows, during the accumulation period, snow reflectivity has a small variation around the average value of 0.8. By contrast, the melting period was characterized by high rates of decrease in reflectivity, the average daily reflectivity being 0.580. Significant or complete melting of snow cover was also noticed in some days, leading to variation in reflectivity from 0.85 to 0.30 in one day.

It should be noted that the duration of accumulation and melting period is highly dependent on the site location and the weather conditions at that site. Multiple criteria, such

as snow cover melting, decreasing rate of reflectivity, and ambient temperature should be considered when deciding the beginning of the melting period. The functional forms of the model, for each period of interest, are presented in Chapter 4.

4 Chapter: Functional form of the model

After performing the exploratory data analysis presented in the previous chapter, the next step was the investigation of various functional forms both linear and non-linear for the model. The functional form of the model was derived using the data set collected during the period August 2017 – April 2018, recorded using the National Instruments PXIe 1078 data logger. The data sample corresponding to this period was divided in two; one set of data was used for deriving the functional form while the other one for validating the model.

Based on the statistical analysis of the error and the goodness of fit corresponding to each trial, the multiple linear regression was found to provide the best prediction. The sample corresponding to each period was divided in two sets of data, each set having approximately the same number of days. One set was used for deriving the functional form of the model and the other one for validating the model. The multiple linear regression was performed using the Data Analysis tool of Microsoft Excel, as well as Matlab. This chapter will present the functional form of the model for each period of interest. A detailed analysis of the error and goodness of fit will be presented further, in Chapter 5.

After the examination of the seasonal variation of reflectivity, presented in Figure 9, and after the exploratory data analysis, it was noticed that significant changes in the decreasing rate of reflectivity could be associated with the following three periods.

4.1 Ground free of snow (short grass covered)

Based on the observations made during the field study, this season can be defined generally as the period starting in the second half of April, until the first half of November, when the ground is generally completely free of snow. For a few days after the end of snow melting period, the ground reflectivity was noticed to experience small daily variations around the value of 0.17, registered around noon. The value, lower than the average 0.2 referenced in literature as characteristic for short grass [7], can be partially explained by the presence of a thin layer of water on the ground surface. At the end of snow melting, due to severe winter conditions, the ground is covered mostly with brown grass, and this might have also a contribution to the lower values of reflectivity. However, while the water percolates into the ground, and the grass starts growing, the reflectivity was noticed to have small variation around the average value of 0.2, also registered around noon.

As was previously said in Chapter 2, the predictors for this period are the zenith angle and sky transmissivity. After performing the multiple linear regression, the resulting functional form of the model was found to have the following expression:

$$\rho = 0.145 + 0.07 \cdot [1 - \cos(\theta_z)] + 0.04 \cdot ST - 0.0009 \cdot (50 - \theta_z) \quad (7)$$

where ρ is the reflectivity, θ_z is solar zenith angle [deg] and ST is sky transmissivity.

From equation 7, it can be noticed that reflectivity increases linearly from a minimum value of 0.145, as a function of solar zenith angle and sky transmissivity. An examination of the observed values of reflectivity led to the conclusion that the value 0.145 occurs most of the times around noon, when the solar zenith angle has the smallest value, under overcast sky conditions. According to the exploratory data analysis results, reflectivity is positively correlated with the solar zenith angle and sky transmissivity, and as such, reflectivity will

have the highest value shortly after sunrise and shortly before sunset, when the solar zenith angle is close to 90 degrees, under clear sky conditions. Analysing the observed values of reflectivity, it was noticed that early in the morning, reflectivity can have frequently values as high as 0.25. Moreover, during the month of November, after cold, clear nights, the reflectivity can reach values as high as 0.3 due to the occurrence of frost on grass.

Additionally, it was noticed that the influence of the solar zenith angle is more significant for values higher than 60 degrees. Comparing the observed values of reflectivity with the predicted ones, for individual days, it was noticed a higher difference in the morning and towards the end of the day, when the solar zenith angle is higher than 80 degrees.

4.2 Snow accumulation or non-melting period

Generally, this period starts at the end of November/beginning of December, when the occurrence of snowfall events is noticed, and ends at the beginning of the active melting of snow. During this period, there are frequent snowfalls and the decrease of reflectivity between two consecutive snowfall events is relatively small. The difference between daily average reflectivity for a day with fresh snow and for the day before a new snowfall event was calculated during this period. The decreasing rate in reflectivity was calculated as the ratio between this difference and the number of days between the two snowfall events. The decreasing rate was in the range of 0.4% to 3.8% per day, with an average of 2.2% per day.

A new variable, snow age (*SA*) was added for the snow accumulation season. The snow age was calculated based on the observations made during the data collection period and recorded in the weather log. Every morning, before starting the data measurement, the

snow age, in hours, was set to a value equal to the number of hours since the last snowfall. The value was increased minutely until the occurrence of a new snowfall event. During the accumulation period, the snow age does not have a significant impact on reflectivity for short time intervals. As Figure 12 illustrates, the effect of snow decay is noticeable from one day to another or for an interval of a few days, between two consecutive snowfall events.

Figure 12. Variation of reflectivity with snow age

As in the case of ground free of snow, a multiple linear regression was performed, and the resulting functional form of the model was found to be the following:

$$\rho = 0.90 - 0.03 \cdot [1 - \cos(\theta_z)] - 0.10 \cdot ST - 0.015 \cdot (SA/24) \quad (8)$$

where ρ is reflectivity, θ_z is solar zenith angle [deg], ST is sky transmissivity and SA is snow age [hours].

From Equation 8, it can be noticed that reflectivity decreases linearly from a maximum value of 0.9, as a function of solar zenith angle, sky transmissivity and snow age. Based on the analysis performed on the observed values of reflectivity, it was noticed that the value 0.9 occurs most of the times when the solar zenith angle has values close to 80 degrees or above, under clear sky conditions. Reflectivity will have the minimum value around noon, when the solar zenith angle has the lowest value, under overcast sky (sky transmissivity lower than 0.3). Reflectivity and snow age are negatively correlated, and as such, reflectivity decreases with the increasing snow age (see Figure 12).

4.3 Snow melting period

Generally, this period is shorter compared with the ground free of snow and snow accumulation period. Snow melting represents the period when changes to the optical properties of the snow cover, the effects of solar radiation penetrating the ground surface, and the development of patchy snow cover, accelerate the decrease in reflectivity. The examination of the observed reflectivity, ambient temperature and the absence of snowfall events led to the conclusion that this period started at the end of February and ended approximately mid-April, when the ground is completely free of snow. Nevertheless, the melting period is highly dependent on the site location and the weather conditions at that site. Multiple criteria, such as snow cover melting, decreasing rate in reflectivity, and ambient temperature should be considered when deciding the beginning of snow melting. For this period, the snowfalls are less frequent and the decrease in reflectivity between two consecutive snowfall events is significant. The analysis of observed reflectivity corresponding to this period led to the conclusion that the decrease in reflectivity has a rate in the range of 0.9% to 47.1% per day. The average daily rate was found to be 17.1%,

significantly higher compared to the accumulation season, when the rate was only 2.2% per day. The end of melting period was established based on the absence of new snowfalls and the values of ambient temperature (no snowfalls for more than 14 days and positive values of ambient temperature for more than 7 days). Contrary to the accumulation season, when the daily variation of reflectivity was noticed to have small values, for the snow melting period, the daily variation was noticed to have a wide range, for some days from 0.85 in the morning, to 0.35 towards the end of the day.

As Figure 13 illustrates, during this period, for most days, the variation with the zenith angle (almost symmetric around noon – red line) is no longer noticeable, and reflectivity is continuously decreasing throughout the day (blue line).

Figure 13. Variation of reflectivity during melting season, compared with snow accumulation season

Observations made during the data collection period led to the conclusion that reflectivity decreases at a lower rate, comparable with the snow accumulation season, in

the morning, when the ambient temperature has generally negative values. The decreasing rate registers significantly higher values compared with the accumulation period once the ambient temperature is larger than a “threshold temperature”.

It was noticed that the value of the threshold temperature is related to the day of the year. Based on the work of McKay [32], who found a relationship between the daily mean temperature above 0°C required for snow melting and the day of the year, the calculation of the threshold temperature was performed using the following expression:

$$T_{threshold} = -0.06 \cdot n + 6.7 \quad (9)$$

where $T_{threshold}$ is threshold temperature, the temperature when the snow melting rate is higher than the melting rate characteristic for the snow accumulation period [°C] and n is day of the year.

For the snow melting period, the predictors were found to be the difference between the ambient temperature and the threshold temperature ($T_a - T_{threshold}$), sky transmissivity (ST) and snow age (SA). Observations made during the data collection period led to the conclusion that reflectivity decreases at a lower rate, comparable with the snow accumulation season, in the morning, when the ambient temperature has generally negative values, and at a significantly higher rate when the ambient temperature is higher than the threshold temperature. The best functional form describing the relationship between variables was found to be a piecewise function having the following expression:

For $(T_a - T_{threshold}) < 0$

$$\rho = 0.75 + 0.085 \cdot ST - 0.022 \cdot (T_a - T_{threshold}) - 0.021 \cdot SA/24 \quad (10)$$

For $(T_a - T_{threshold}) > 0$

$$\rho = 0.90 + 0.115 \cdot ST - 0.008 \cdot (T_a - T_{threshold}) - 0.041 \cdot SA/24 \quad (11)$$

where ρ is reflectivity, ST is sky transmissivity, T_a is ambient temperature [$^{\circ}\text{C}$], $T_{threshold}$ is threshold temperature [$^{\circ}\text{C}$], and SA is snow age [hours].

From equations (10) and (11), it can be noticed that the influence on snow age is significantly higher compared with the accumulation season (the coefficients corresponding to snow age are 0.021 when ambient temperature is lower than the threshold temperature and 0.041 when ambient temperature is higher than the threshold temperature, respectively, while for the accumulation period the coefficient is 0.015). Observations made during the data collection led to the conclusion that the decrease in reflectivity of late-occurring snow is significantly higher compared with the accumulation period, resulting in high variability from one day to another. The highest decrease in reflectivity was noticed to be when patches of bare ground are visible through the snow cover, and the fraction of incoming solar radiation absorbed is increasing. However, this transition period was noticed to be relatively short, spanning only 1 or 2 days.

5 Chapter: Testing the model fit and error analysis

After deriving a functional form for each period of interest (ground free of snow, snow accumulation, and snow melting), the next step was to perform a statistical analysis to assess the bias of the model. The model was tested by comparing its predictions with the observed values of reflectivity for each analysed period.

5.1 Statistics performed to assess model fit and residuals

The regression model involves predicting a continuous valued output (response) based on a set of input variables (predictors). The difference between the response predicted by the model and the actual observed value from the measured data is called the residual for each point, and residuals refers collectively to all of the differences between all predicted and actual values [31]. For each period of interest: ground free of snow, snow accumulation and snow melting, the following methods were applied to evaluate how fit the model is and the accuracy of its predictions:

5.1.1 Visual evaluation of the model fit

Graphs are appropriate tools for assessing broad qualitative trends of the data and they provide an excellent manner of communicating to the reader what the author wishes to state or illustrate [30]. A common and simple approach to evaluate models is to regress

measured/observed versus predicted values and compare against the 1:1 line. According to theory, for a model providing good agreement between measured/observed outcomes and predictions, the points should be distributed along the 1:1 line, as Figure 14, illustrates.

The analysis of residuals can provide also valuable information about the model. More specifically, the plot of residuals versus the predicted values may provide information about the appropriateness of the linear regression model. In the case of a good agreement between the measured/observed values and the predicted ones, the distribution of residuals should have the following properties:

- The residuals are scattered randomly around the $y = 0$ line, proving this way that the assumption of a linear relationship between variables is reasonable.
- The residuals roughly form a horizontal band around the $y = 0$ line, suggesting that the variances of the error terms are equal.
- No one residual stands out from the basic random pattern of residuals, signifying that there are no outliers.

Figure 15 illustrates the plot of residual versus predicted values for a model providing a good agreement between the measured/observed values and the predicted ones [33].

Figure 14. Distribution of measured versus predicted values for an ideal model

Figure 15. Distribution of residuals versus predicted values for an ideal model

Among the statistics used in Ordinary Least Squares (OLS) regression to evaluate model fit are the following: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and R-squared [30].

5.1.2 Statistics used to evaluate the model fit

Root mean square error (RMSE)

The RMSE is the square root of the variance of the residuals.

$$RMSE = \sqrt{\frac{\sum (y_i - \hat{y}_i)^2}{N}} \quad (12)$$

where y_i is observed reflectivity, $\hat{y}_i$ is predicted reflectivity, and N is the number of data points.

RMSE indicates the absolute fit of the model to the data—how close the observed data points are to the values predicted by the model. As the square root of a variance, RMSE can be interpreted as the standard deviation of the unexplained variance and has the useful property of being in the same units as the response variable. Lower values of RMSE indicate better fit. RMSE is a good measure of how accurately the model predicts the response and is the most important criterion for fit if the main purpose of the model is prediction [30].

Mean absolute error (MAE)

The mean absolute error (MAE) is defined as the mean absolute difference between the actual data values and model predicted values [30]:

$$MAE = \frac{(\sum |y_i - \hat{y}_i|)}{N} \quad (13)$$

where y_i is observed reflectivity, $\hat{y}_i$ is predicted reflectivity, and N is the number of data points.

R² and Adjusted R²

R² is the proportional improvement in prediction from the regression model, compared to the mean model (using the average of observed data). It indicates the goodness of fit of the model [30].

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y}_i)^2} \quad (14)$$

where y_i is observed reflectivity, $\hat{y}_i$ is predicted reflectivity, and $\bar{y}_i$ is average observed reflectivity.

R² has the useful property that its scale is intuitive: it ranges from zero to one, with zero indicating that the proposed model does not improve prediction over the mean model and one indicating perfect prediction. Improvement in the regression model results in proportional increases in **R²**. In some situations, **R²** can be misleading because it can only increase as predictors are added to the regression model. This increase is artificial when predictors are not actually improving the model [31]. To compensate for this, a related statistic, adjusted **R²**, incorporates the degrees of freedom of the model.

$$\overline{R^2} = 1 - (1 - R^2) \frac{N - 1}{N - k} \quad (15)$$

where N is the total number of observations and k is the number of model parameters.

Adjusted **R²** will decrease as predictors are added if the increase in model fit does not justify the loss of degrees of freedom. Likewise, it will increase as predictors are added if the increase in model fit is worthwhile. Adjusted **R²** should always be used with models with more than one predictor variable. It is interpreted as the proportion of total variance that is explained by the model. There are situations in which **R²** is not always relevant. When the interest is in a relationship between variables for prediction, not in fitting the

results to a specific set of data, the R^2 is less important [30].

The results of the goodness of fit and error analysis, for each period of interest, are presented further.

5.1.3 Ground free of snow (short grass covered)

As was explained in Chapter 2, during the exploratory data analysis, the data was manually sorted in three bins: days with clear sky (sky transmissivity higher than 0.6 most of the time), days with mixed sky or intermittent cloudiness (sky transmissivity between 0.3 – 0.6), and days with overcast sky (sky transmissivity lower than 0.3 most of the time).

After deriving the functional form of the model, the observed and predicted reflectivity were plotted versus zenith angle, to visually investigate the goodness of fit. Analyzing the trends of individual days for this period, it was noticed that for most days with clear and mixed sky, the model is slightly overpredicting the reflectivity at the beginning and the end of the day (high values of the solar zenith angle). For days with overcast sky, especially during rain, when sky transmissivity has very low values (many times lower than 0.1), the difference between the observed and predicted values was noticed to be higher. Typically, for these time intervals the solar radiation has very low values, and as such, the error introduced in the calculation of solar radiation incident on surfaces of various orientations might be insignificant. This aspect will be explored in more depth in Chapter 8.

Nevertheless, it can be said that a good agreement between the observed and predicted reflectivity was noticed for most days. Figure 16 illustrates the trends of observed and predicted reflectivity for three representative days: clear sky, mixed sky and overcast sky.

Figure 16. Measured/predicted reflectivity versus solar zenith angle for representative days

After the visual assessment of individual days, the statistical methods presented in Section 5.1 were applied in order to assess the model. Figure 17 presents the graph of observed versus predicted reflectivity, and Figure 18 illustrates the distribution of residuals versus predicted reflectivity.

Figure 17. Measured versus predicted reflectivity

Figure 18. Residuals versus predicted reflectivity

According to Figure 17, the points are symmetrically distributed along the 1:1 line, and relatively close, indicating that the model provides good agreement between observations and predictions. Additionally, according to Figure 18, the residuals are scattered randomly around the $y = 0$ line, suggesting that the linear relationship assumption is reasonable, and the majority is in the range $[-0.05, 0.05]$. Most values standing out from the random pattern (outliers) correspond to a day with overcast sky and heavy rain, when sky transmissivity was noticed to have values lower than 0.1.

The analysis of residuals shows that $RMSE = 0.015$, $MAE = 0.011$, and $R^2 = \overline{R^2} = 0.652$. It can be noticed that both RMSE and MAE have values very close to the measurement error ($\pm 5.7\%$), indicating a good agreement between observed and predicted data. As previously was said, the adjusted R-squared is a relative measure of fit and its value should be close to 1. However, when the goal is to use the model for prediction, its value becomes less relevant, and even though the adjusted R-squared is not very close to 1, as long as the trends of predicted and observed values are in good agreement, the model can be considered fit [30].

Additionally, other descriptive statistics such as mean, standard deviation, variance were calculated using the Data Analysis tool of Microsoft Excel. One of the assumptions for regression analysis was that the residuals are normally distributed. To assess this assumption, the normal probability plot of residuals was done. Both descriptive statistics and the histogram of residuals show that the residuals are normally distributed. The results are presented in Appendix E.

5.2 Snow accumulation or non-melting period

A similar analysis, as in the case of ground free of snow, was performed for the snow accumulation period. After deriving the functional form of the model, the observed and predicted reflectivity were plotted versus zenith angle, to visually investigate the goodness of fit. It was noticed a good agreement between the observed and predicted reflectivity for most days. Figure 19 illustrates the trends of observed and predicted reflectivity for three representative days: clear sky, mixed sky and overcast sky.

Figure 19. Measured/predicted reflectivity versus solar zenith angle for representative days

Analysing the trends of individual days, it was noticed that for most days with mixed and overcast sky, the predicted values of the model follow the trend of observed data, and they fit between the lines of measurement error most of the time. However, in the case of days with clear sky, there are noticeable differences between the trends of observed and

predicted data. The bias of the model can be explained partly by the small number of full sunny days during the data collection period. Despite efforts made to construct the most representative data sample, the number of entries with mixed and overcast sky are dominant.

After the visual assessment of individual days, the statistical methods presented in Section 5.1 were applied in order to assess the model fit. Figure 20 presents the graph of observed versus predicted reflectivity, and Figure 21 illustrates the distribution of residuals versus predicted reflectivity. According to Figure 20, the points are quite symmetrically distributed along the 1:1 line, and relatively close, indicating that the model provides good agreement between observations and predictions. Additionally, according to Figure 21, the residuals are scattered randomly around the $y = 0$ line, suggesting that the linear relationship assumption is reasonable, and the majority is in the range $[-0.1, 0.1]$. Despite efforts made to clean the data, there are a few residuals standing out from the basic random pattern, suggesting that these values are outliers.

Figure 20. Measured versus predicted reflectivity

Figure 21. Residuals versus predicted reflectivity

The analysis of residuals shows that $RMSE = 0.041$, $MAE = 0.031$, and $R^2 = \overline{R^2} = 0.665$. It can be noticed that both RMSE and MAE have values higher than in the case of ground free of snow. As was presented in literature review, for the winter season there are other factors such as snow grain size, accumulation of light absorbing particles or spectral composition of light which might have a significant effect on snow reflectivity, and may account for part of the error. However, both RMSE and MAE have values smaller than the measurement error ($\pm 5.7\%$), indicating in this case too, a good agreement between the observed and predicted data. The adjusted R-squared is not very close to 1, but as previously was said, as long as the predicted trend closely follows the observed one, the model can be considered fit.

As in the case of ground free of snow, other descriptive statistics such as mean, standard deviation, variance were calculated using the Data Analysis tool of Microsoft Excel. The normal distribution of the residuals was also checked. Both descriptive statistics and the histogram of residuals show that the residuals are very close to normal distribution. The results are presented in Appendix E.

5.3 Snow melting period

The analysis performed in the case of ground free of snow and snow accumulation was performed also for the snow melting season. After deriving the functional form of the model, the observed and predicted reflectivity were plotted versus time, to visually investigate the goodness of fit. As presented in Section 4.3, for the snow melting period, the effect of the zenith angle is no longer noticeable, and the reflectivity has a continuously decreasing trend for all types of sky.

Figure 22 illustrates the trends of observed and predicted reflectivity for three representative days: clear sky, mixed/overcast sky and discontinuous snow cover/overcast sky. It was noticed that the predicted values of the model follow the trend of observed data for most days, and for all types of cloud cover. However, in the case of discontinuous snow cover, when the solar radiation absorbed by the ground increases (leading to a higher snow melting rate), there are noticeable differences between the trends of observed and predicted data. Nevertheless, as was previously said, the number of such days is very small compared with the total number of days, and as such, their overall influence might be insignificant.

Figure 22. Measured/predicted reflectivity versus time for representative days

After the visual assessment of individual days, the statistical methods presented in Section 5.1 were applied in order to assess the model fit. Figure 23 presents the graph of observed versus predicted reflectivity, and Figure 24 illustrates the distribution of residuals

(residuals versus predicted reflectivity). According to Figure 23, the points are distributed along the 1:1 line but the spread is higher than in the previous two cases, indicating a higher error. Additionally, according to Figure 24, the residuals are scattered randomly around the $y = 0$ line, suggesting that the linear relationship assumption is reasonable. However, even though most residuals fall in the range $[-0.1, 0.1]$, there are some points displaying higher errors, most of them corresponding to days with discontinuous snow cover. It can be noticed also that clusters of points are clearly distinguishable among residuals, indicating different variances among the data in the sample.

Figure 23. Measured versus predicted reflectivity

Figure 24. Residuals versus predicted reflectivity

The analysis of residuals shows that $RMSE = 0.071$, $MAE = 0.057$, and $R^2 = \overline{R^2} = 0.673$. It can be noticed that the RMSE is slightly higher than the measurement error, while the MAE has the same value as the measurement error. According to literature, for the winter season there are other factors such as snow grain size, accumulation of light absorbing particles or spectral composition of light which might significantly affect the reflectivity, and they may account for part of the error.

Using the Data Analysis tool of Microsoft Excel, other descriptive statistics such as mean, standard deviation, variance were calculated also for this period. The normal distribution of the residuals was checked, as in the case of ground free of snow and snow accumulation. Both descriptive statistics and the histogram of residuals show that in this case, the residuals are no longer normally distributed. The results are presented in Appendix E.

In addition to daily comparison of the observed and predicted reflectivity, monthly averages were also calculated and compared, for a whole year, attempting to quantify the difference between the predicted and measured values for longer time intervals. The results of this comparison are presented in Table 4.

Table 4. Measured and predicted monthly averages

Month	Observed Reflectivity	Measurement Uncertainty	Predicted Reflectivity	Difference between predicted and observed
January	0.804	± 0.046	0.818	-0.014
February	0.768	± 0.044	0.784	-0.016
March	0.618	± 0.035	0.715	-0.097
April	0.205	± 0.017	0.204	+0.001
May	0.216	± 0.018	0.215	+0.001
June	0.208	± 0.017	0.220	-0.012
July	0.215	± 0.018	0.212	+0.003
August	0.197	± 0.011	0.207	-0.010
September	0.194	± 0.011	0.215	-0.021
October	0.197	± 0.011	0.213	-0.016
November	0.284	± 0.016	0.312	-0.028
December	0.543	± 0.030	0.532	+0.011

As Table 4 illustrates, there is a good agreement between the monthly averages of observed and predicted data, the difference being in all cases smaller than the measurement error.

6 Chapter: Model validation

In the previous chapter was presented the analysis performed to assess how the predictions of the model compare with the observed data, using the same set of data as for deriving the functional form of the model. Further, the model will be validated using a new set of data.

Validation studies are usually performed in order to uncover the weaknesses and limitations of a model, as well as to identify potential improvements. Even when the main causes of the difference between the measured and predicted values are known, it is useful to determine the value of uncertainty associated with the model [21].

A simple and intuitive way of performing validation for the model is to use the so-called "split-sample" procedure [30]. As was explained in Chapter 2, the observed data were divided in two sets: one set was used for developing the model and the other one was used to test/validate the model. The procedure was repeated by inverting the group of data used for deriving the model and validation, therefore obtaining two validation tests. The similarity or dissimilarity of the parameter values in different calibration procedures provides an indication of the reliability of the estimates. The parameter values generated by the validation data set were compared with the ones provided by the data set used for the model. The parameters of the final functional form to be implemented in ESP-r were found by using the whole data sample, to reduce the uncertainty of the parameter estimates as much as possible.

As in the case of the analysis performed for developing the model, graphs and descriptive statistics were used for assessing the broad qualitative trends of the data. The results for each period are presented in the following sections.

6.1 Ground free of snow (short grass covered)

The set of validation data (second half of the sample) was used to predict the reflectivity employing the functional form of the model derived based on the first half of the sample. The observed and predicted reflectivity were plotted versus zenith angle, to visually investigate the goodness of fit. It was noticed a good agreement between the observed and predicted reflectivity for most days. Figure 25 illustrates the trends of observed and predicted reflectivity for three representative days: clear sky, mixed sky and overcast sky.

Figure 25. Measured/predicted reflectivity versus solar zenith angle for representative days

After analysing the trends of individual days, it was noticed that for most days with clear and mixed sky, the model is slightly overpredicting the reflectivity at the beginning and at the end of the day. For days with overcast sky, when sky transmissivity has very low values (many times lower than 0.1), the values predicted by the model display a higher difference compared with the measured ones. Usually, for these time intervals the solar radiation has very low values, and as such, the error introduced in calculation of the solar radiation incident on surfaces of various orientations might be insignificant. As was stated in Section 5.1.3, this aspect will be explored in more depth in Chapter 8.

Figure 26 illustrates the correlation between the measured and predicted data, while Figure 27 displays the distribution of residuals.

Figure 26. Observed versus predicted reflectivity

Figure 27. Residuals versus predicted reflectivity

According to Figure 26, the points are closely and symmetrically distributed along the 1:1 line, indicating that the model provides good agreement between the derived measurements and predictions. Additionally, according to Figure 27, the residuals are scattered randomly around the $y = 0$ line, suggesting that the linear relationship assumption

is quite reasonable. However, even though most residuals tend to cluster around the $[-0.05, +0.05]$ range of the y-axis, the horizontal band around the line $y = 0$ is not very even, indicating that the variances of the error terms are not equal. It can be noticed also, that despite efforts to clean the data, there are a few residuals standing out from the basic random pattern, suggesting that these values are outliers.

The analysis of residuals shows that $RMSE = 0.021$, $MAE = 0.017$, and $R^2 = \overline{R^2} = 0.611$. It can be noticed that both RMSE and MAE corresponding to the validation data set have values higher than those corresponding to the data set used to derive the model (0.015 and 0.011, respectively). However, even though both are higher than the measurement uncertainty ($\pm 5.7\%$), a good agreement was noticed between the observed and predicted data.

6.2 Snow accumulation or non-melting period

As in the previous case, for the snow accumulation season, the observed and predicted reflectivity were plotted versus zenith angle, to visually investigate the goodness of fit. Figure 28 illustrates the trends of observed and predicted reflectivity for three representative days: clear sky, mixed sky and overcast sky.

A good agreement between the observed and predicted reflectivity was noticed for most days, by assessing the trends for individual days. For days with clear sky, the model alternates between periods when reflectivity is underpredicted and periods when it is overpredicted.

Figure 28. Measured/predicted reflectivity versus time for representative days

Figure 29 illustrates the correlation between the measured and predicted data for the validation sample, while Figure 30 presents the plot of residuals versus the predicted reflectivity.

Figure 29. Measured versus predicted reflectivity

Figure 30. Residuals versus predicted reflectivity

According to Figure 29, measured versus predicted reflectivity, the points have a fairly close and symmetric distribution along the 1:1 line, indicating that the model provides good agreement between the observed and predicted data. The cluster of points noticed to be further from the 1:1 line corresponds to a freezing rain day. This phenomenon resulted in values of reflectivity up to 0.15 lower than the usual values for fresh snow (an average value of 0.77 compared with 0.85 characteristic for fresh snow) for at least one week, when the next snowfall event occurred.

Additionally, according to Figure 30, residuals versus predicted reflectivity, the residuals are scattered relatively randomly around the line $y = 0$, suggesting that the linear relationship assumption is quite reasonable. However, even though most residuals tend to cluster around the $[-0.05, +0.05]$ range of the y-axis, the horizontal band around the line $y = 0$ is not very even, indicating that the variances of the error terms are not equal. The cluster of points corresponding to freezing rain can be noticed in distribution of residuals also, the error having in this case negative values, significantly lower than -0.05 .

The statistical analysis of residuals shows that $RMSE = 0.050$, $MAE = 0.038$, and $R^2 = \overline{R^2} = 0.621$. It can be noticed that both RMSE and MAE corresponding to the validation data set have values slightly higher than those corresponding to the data set used to derive the model (0.0141 and 0.031, respectively). However, both are still smaller than the measurement error ($\pm 5.7\%$), indicating a good agreement between the observed and predicted data.

6.3 Snow melting period

The 2018 snow melting season was noticed to be short, and as such the sample of observed

data was not large enough to be divided in two sub-sets. For the validation of the model a sample containing some days of the 2017 melting season was used. Figure 31, presented further, illustrates the trends of observed and predicted reflectivity for three representative days: clear sky, mixed sky and overcast sky.

A good agreement between the observed and predicted reflectivity was noticed for most days, by analysing the individual trends. As in the case of study performed for model development, the highest difference was noticed for days when the snow cover is no longer continuous, and patches of ground can be seen through the snow cover.

Figure 31. Measured/predicted reflectivity versus time for representative days

Figure 32 illustrates the correlation between the measured and predicted data for the validation sample, while Figure 33 presents the plot of residuals versus the predicted reflectivity. According to Figure 32, measured versus predicted reflectivity, most points

have a fairly close and symmetric distribution along the 1:1 line, indicating that the model provides good agreement between the observed and predicted data.

Figure 32. Measured versus predicted reflectivity

Figure 33. Residuals versus predicted reflectivity

However, as in the case of model development, there are a few days with discontinuous snow cover, when the difference between the observed and predicted data is higher. Additionally, according to Figure 33, the residuals are scattered relatively randomly around the line $y = 0$, suggesting that the linear relationship assumption is quite reasonable. Still, even though most residuals tend to cluster around the $[-0.1, +0.1]$ range of the y-axis, the horizontal band around the line $y = 0$ is not very even, indicating that the variances of the error terms are not equal.

The statistical analysis of residuals shows that $RMSE = 0.075$, $MAE = 0.062$, and $R^2 = \overline{R^2} = 0.646$. It can be noticed that both RMSE and MAE corresponding to the validation data set have values slightly higher than those corresponding to the data set used to derive the model (0.071 and 0.057, respectively). However, both are still smaller than the measurement error ($\pm 8.4\%$), indicating a good agreement between the observed and predicted data.

7 Chapter: Building performance simulation in ESP-r

7.1 Short description of ESP_r

ESP-r is an open-source building performance simulation tool developed by the Energy Systems Research Unit (ESRU) at the University of Strathclyde, Scotland. It is a general purpose, multi-domain simulation environment which has been the subject of sustained developments since 1974. The software can simulate building thermal behaviour, inter-zone air flow, intra-zone air movement, HVAC systems and electrical power flow. The simulation process follows description, and additional technical domain solvers can be invoked as the building and system description evolve [34].

ESP-r allows the user to define both the resolution and extent of the model, from the room level to a neighborhood, to address the specific needs of a project. Users have options to set the geometric, environmental control and operational complexity of models to match the requirements of specific projects.

ESP-r is distributed as a collection of tools. A project manager controls the development of models and requests computational services from other modules in the set as well as 3rd party tools. Some of the supported modules include:

- prj — the project manager facility;
- bps — an integrated (all domain) simulation engine;
- res — a graphic simulation predictions display and reporting tool;

clm — a weather display/analysis/conversion tool;

ish — a shading and insolation pre-processor and display tool;

vwf — a surface-to-surface and MRT sensor body view factor calculation tool.

ESP-r allows an in-depth appraisal of the factors which influence the energy and environmental performance of buildings, attempting to simulate the real world as rigorously as possible and to a level which is consistent with current best practice. By addressing all aspects simultaneously, ESP-r allows the designer to explore the complex relationships between a building's form, fabric, air flow, plant and controls. ESP-r is based on a finite volume, conservation approach in which a problem (specified in terms of geometry, construction, operation, leakage distribution, etc.) is transformed into a set of conservation equations (for energy, mass, momentum, etc.) which are then integrated at successive time-steps in response to climate, occupant and control system influences [34].

7.2 Treatment of solar radiation incident on an external surface

Solar or short-wave radiation is radiation originating from the sun, in the wavelength of 0.3 to 3 μm [12]. ESP-r operates with total and hemispherical quantities of solar radiation. The total solar radiation incident on an external surface of a building can be calculated as the sum of three components: the beam component $I_{\beta b}$, originating from the solar disc; the diffuse component, $I_{\beta d}$, originating from the sky dome; and the ground reflected component $I_{\beta g}$, originating from the ground in front of the surface of interest [7]. Figure 33 illustrates the beam, diffuse and ground reflected components of the solar radiation incident on a sloped surface.

Figure 34. Solar radiation incident on a sloped surface (adapted from [7])

$$\left\{ \begin{array}{l} \text{Incident} \\ \text{solar} \\ \text{radiation, } I_{\beta} \end{array} \right\} = \left\{ \begin{array}{l} \text{Direct} \\ \text{beam} \\ \text{radiation, } I_{\beta b} \end{array} \right\} + \left\{ \begin{array}{l} \text{Sky} \\ \text{diffuse} \\ \text{radiation, } I_{\beta d} \end{array} \right\} + \left\{ \begin{array}{l} \text{Ground} \\ \text{reflected} \\ \text{radiation, } I_{\beta g} \end{array} \right\} \quad (16)$$

The solar radiation is generally read from weather files, which provide the following two options:

- Direct normal solar irradiance and diffuse horizontal solar irradiance;
- Global horizontal solar irradiance and diffuse horizontal solar irradiance.

The direct solar radiation incident on the inclined surface is related to the direct normal solar radiation through the following relationship:

$$I_{\beta b} = I_b \cdot \cos(\theta_i) \quad (17)$$

where $I_{\beta b}$ is the direct solar radiation incident on the inclined surface, I_b is the direct normal solar radiation, and θ_i is the angle of incidence of the beam radiation on the surface [7].

In ESP-r, the diffuse component can be calculated using either an isotropic or an

anisotropic model. The isotropic model assume that the intensity of diffuse sky radiation is uniform over the sky dome. Hence, the diffuse radiation incident on a tilted surface depends on a fraction of the sky dome seen by the respective surface. The anisotropic model (Perez and al., 1990), which is the default model, assumes anisotropy of the diffuse sky radiation due to the circumsolar region (sky near the solar disk) and the isotopically distributed diffuse component from the rest of the sky dome (horizon brightening fraction) [35]. In general, the diffused fraction of radiation on inclined surfaces is calculated using the relationship:

$$\left\{ \begin{array}{c} \text{Diffuse} \\ \text{irradiance} \\ \text{on surface} \end{array} \right\} = \left\{ \begin{array}{c} \text{Diffuse} \\ \text{irradiance} \\ \text{from sky} \\ \text{dome} \end{array} \right\} + \left\{ \begin{array}{c} \text{Diffuse} \\ \text{irradiance} \\ \text{from circumsolar} \\ \text{region} \end{array} \right\} + \left\{ \begin{array}{c} \text{Diffuse} \\ \text{irradiance} \\ \text{from sky} \\ \text{horizon} \end{array} \right\} \quad (18)$$

$$I_{\beta d} = I_{dh}[(1 - F_1) \cdot \frac{1 + \sin\beta}{2} + F_1 \cdot \frac{a}{b} + F_2 \cdot \cos\beta] \quad (19)$$

where: $I_{\beta d}$ is the diffuse solar radiation incident on the inclined surface, I_{dh} is the diffuse horizontal solar radiation, F_1 is the circumsolar brightening coefficient, F_2 is the horizon brightening coefficient, β is the slope of the surface, and a , b are correction factors for the angle of incidence of circumsolar radiation [35].

The coefficients a and b can be calculated using the following equations:

$$a = \max[0, \cos(\theta_i)]; \cos(\theta_i) = \frac{I_{\beta d}}{I_d} \quad (20)$$

$$b = \max[\cos(85^\circ), \cos(\beta_s)]; \sin(\beta_s) = \frac{I_{dh}}{I_d} \quad (21)$$

where: θ_i is the angle of incidence of the beam radiation on the inclined surface, and β_s is the solar altitude [35].

For calculating the ground reflected component, the ground is considered to be a diffuse

reflector. The ground reflected component of irradiance is calculated using the following relationship:

$$I_{\beta g} = F \cdot \rho_g \cdot I_{gh} \quad (22)$$

where: $I_{\beta g}$ is the ground reflected solar radiation incident on the inclined surface, I_{gh} is the global horizontal solar radiation, F is the view factor taking into account how the ground is viewed from the surface, and ρ_g is ground reflectivity [7].

The global horizontal solar radiation is calculating using the equation:

$$I_{gh} = I_b \cdot \cos(\theta_z) + I_{dh} \quad (23)$$

where: I_{gh} is the global horizontal solar radiation, I_{dh} is the diffuse horizontal solar radiation, and θ_z is the zenith angle.

For flat surfaces, the view factor, F is calculated with the following geometric formula:

$$F = \frac{1 - \cos\beta}{2} \quad (24)$$

where: β is the slope of the surface [7].

7.3 Energy balance at an external surface

ESP-r uses a finite difference, heat balance approach to perform thermal simulations of the building. First step is the discretization of the building's envelope, air volumes, solid-fluid interfaces and plant components, by placing nodes along the main directions of heat flow in the building, as Figure 34 illustrates. Discretization simplifies the continuous differential equations describing the heat balance of the building's components into a series of discrete equations, which are suitable for numerical computation. By default, ESP-r assumes one-dimensional heat transfer and the nodes are placed accordingly. For multi-layer constructions, the nodes are placed within each construction layer to account for the

different thermal properties of each layer. The number of nodes within a layer can be specified by the user.

Figure 35. Discretization of the exterior surface
(adapted from [36])

Figure 36. Heat balance at the exterior surface
(adapted from [36])

The second step is to place a control volume around each node, and to write the corresponding heat balance equation, considering only the relevant heat flows through a node. ESP-r uses the Crank-Nicolson finite differencing scheme to approximate these equations. The Crank-Nicolson scheme is a weighted average between implicit and explicit finite differencing. By default, equal weightings to the explicit and implicit terms are assigned; however, weighting can also be user-specified. The explicit finite differencing formulation expresses the solution for the present time using quantities from the previous time step, while the implicit formulation expresses the solution for the present time step using present quantities. The derived, Crank-Nicolson heat balance equations feature present temperatures (known) and future temperatures (unknown). The heat balance equations relate each node to its neighbours, resulting in a system of interconnected finite difference equations. Figure 35, previously presented, illustrates the relevant heat flows at the external surface of a building. The energy balance has the following components:

$$\left\{ \begin{array}{c} \text{Storage} \\ \text{of energy} \\ \text{in CV} \end{array} \right\} = \left\{ \begin{array}{c} \text{Solar} \\ \text{radiation} \\ \text{absorbed} \end{array} \right\} - \left\{ \begin{array}{c} \text{Convection} \\ \text{to} \\ \text{environment} \end{array} \right\} - \left\{ \begin{array}{c} \text{Net longwave} \\ \text{radiation to} \\ \text{environment} \end{array} \right\} - \left\{ \begin{array}{c} \text{Conduction} \\ \text{toward} \\ \text{inside} \end{array} \right\} - \left\{ \begin{array}{c} \text{Conduction} \\ \text{to} \\ \text{ground} \end{array} \right\} \quad (25)$$

The third step is to simultaneously solve the system of finite difference equations, using matrix inversion, to determine the temperature of each node and the heat flows between the nodes. The second and third steps are repeated at the start of each simulation time step.

7.4 Weather data for building performance simulation

Driving building performance simulation models requires short-interval environmental data, which provide the boundary conditions for the model. Ideally, environmental data should be observed at the project site, subject to local conditions, and the observations should be made at intervals consistent with the simulation time step. However, in reality, these ideals are rarely reached [37].

Traditionally, weather data for simulation have been represented in files of values for the 8760 hours of a year (or 8784 hours for a leap year). Conventional procedures for constructing hourly records use instantaneous values or integrated values from the preceding half hour to the next half hour for meteorological data (such as temperatures, humidity, and wind speed) and integrated quantities over the prior hour for solar and illuminance data [37].

Among the most common modeling applications is full-year hourly simulation to calculate the energy use. Extensive effort has been applied to finding representative or typical weather years that allow estimation of long-term (multi-year) performance from a single year analysis. The Typical Meteorological Year (TMY) is a composite of typical months, not necessarily from the same year, and it is most of the time used for predicting

energy use. Currently, the weather file format is TMY3 or EPW. Both are comma separated files and include metadata (such as site location) and column headings [37].

Many of the weather files distributed with ESP-r are sourced from EPW files. For sites which are not included in the distribution, ESP-r provides facilities to convert downloaded EPW files. ESP-r weather data is composed of a header which defines site information - name, year, latitude, longitude (degrees from the local time meridian) and a tag which defines whether solar data is measured as direct normal or global horizontal. Generally, the parameters describing the weather have a temporal resolution of one hour. Sub-hourly weather data can be accommodated via a temporal file. At each hour the weather data comprises diffuse horizontal solar radiation, dry bulb temperature, direct normal or global horizontal solar radiation, wind speed and wind direction. There are no entries for cloud type, cloud percentage, dew point, precipitation (or snow) or ground temperatures. Conventional procedures for constructing hourly records use instantaneous values for meteorological data such as: temperature, humidity, and wind speed, and totals over the prior hour for solar and illuminance data [34].

For time steps shorter than one hour, the weather data are linearly interpolated for each time step, excepting the solar radiation. In the case of solar radiation, using the half-hour centred option of ESP-r, the solar irradiance in the weather file is taken to represent the irradiance at the preceding half hour. As such, the system is doing a double interpolation for calculating the solar radiation at times between 12:00 and 12:30, for example. First, the average value between 12:00 and 13:00 is calculated for 12:30; further, the values of solar radiation for each time step are calculated using the linear interpolation between the value of solar radiation at 12:30 and the value of solar radiation at 13:30.

In order to quantify the impact of the model, a full-year hourly simulation to calculate

the solar radiation incident on various surfaces is required. However, since the predictions will be compared with measured data, collected at the CHEER site, a weather file with real data is required instead of the typical year. An EPW file was adapted with hourly weather data available at the CHEER site. The missing data were replaced by information provided by Environment Canada.

7.5 Implementation of the model in ESP-r source code

As was presented in Section 7.1, ESP-r is distributed as a collection of tools/modules. A project manager controls the development of models and requests computational services from other modules. The BPS module is an integrated (all domain) simulation engine, and the SOLAR.F file, responsible for the solar calculation is part of this module. The algorithm for ground reflectivity calculation is called MZGREF and it was modified to include the new model.

The inputs required by the model are the solar zenith angle and sky transmissivity for the ground free of snow season, and the solar zenith angle, sky transmissivity, snow age, and the difference between the ambient temperature and the threshold temperature calculated using Equation (9) (page 65), for the snow-covered ground season.

The solar module of ESP-r has the capability of calculating the solar zenith angle. Employing the values of the zenith angle provided by the solar module, and the Equations (4) and (5) (page 41), the algorithm will calculate the sky transmissivity for each time step. Further, using the functional form characteristic for the ground free of snow period, the reflectivity will be calculated for each time step of the simulation process.

In order to switch from the period when the ground is free of snow to the period when the ground is covered with snow, a logical variable called SNOW will be used. When no

snowfall event is detected SNOW=FALSE, while when the presence of a new snowfall event is detected SNOW=TRUE. The presence of snowfall will be predicted by the algorithm based on the values of dry bulb temperature, relative humidity, and atmospheric pressure recorded in the weather file used to drive the simulation. When snow is detected the algorithm will start counting the snow age for every time step.

If the presence of snow is detected for more than three hours (based on the observations made during the data collection period, this represents the time required for snow depth to reach at least 2.5 cm) the algorithm switches from the ground free of snow model to the snow accumulation model. Based on the calculated values of zenith angle, sky transmissivity and snow age, the algorithm will predict the reflectivity for each time step of the simulation.

The beginning of the snow melting period will be detected based on the threshold temperature value, calculated using equation (9) (page 65). The algorithm will calculate the threshold temperature, and when the ambient temperature is below the threshold temperature, the algorithm will use the functional form having a smaller melting rate, while when the ambient temperature is above the threshold temperature the algorithm will use the functional form having a higher melting rate. When the reflectivity drops to the value 0.3, characteristic for ground free of snow, the algorithm changes the snow melting functional form to the ground free of snow form.

Figure 36 presents the flow chart of the algorithm developed for implementing the new model. The FORTRAN code developed for implementing the new model in ESP-r source code is presented in Appendix F.

Figure 37. Flow chart diagram of the algorithm

8 Chapter: Impact of the model on estimation of solar irradiance incident on various surfaces

Ground-reflected solar radiation has high values for surfaces having unobstructed views of the ground (such as vertical walls and windows). Solar irradiance incident on surfaces of various slopes is important for predicting both the performance of a building as well as the performance of a solar technology. In this context, to assess the impact of the new model, two sets of simulations were performed with ESP-r:

- Estimation of the solar irradiance incident on a south-oriented façade, very important for passive solar design, and
- Estimation of the solar irradiance incident on a surface with a 60° slope.

8.1 Urbandale Centre simplified model

Generally, the approach taken to create the geometry of a model depends on the questions to address with the model, the availability of input data, as well as on the time constraints. Since the main task of the simulation is the estimation of the solar irradiance incident on the south façade and on the roof (surface with a 60° slope) of the CHEeR house, the actual geometry of the building was simplified/abstracted, in order to decrease the number of uncertainties and to save time. Although detailed construction drawings and specifications of the CHEeR house were available, the construction types and materials existing in the ESP-r databases were used for the model [38]. The house was divided in two zones (one

zone for ground and main floors and one for the attic), and the basement was not taken into account. The simulations were performed under free floating conditions.

Figure 38. Wireframe representation of the Urbandale Centre model in ESP-r

8.2 Estimation of solar irradiance incident on the south façade

To demonstrate the ability of the model to calculate the net radiation incident on a south oriented facade, the predictions of the model were compared with measured values of solar irradiance, for the period January – December 2017. As was previously presented, the data collected between December 2016 and July 20, 2017 were used for the exploratory analysis, while the data collected for the period July 21 – December 2017 were use for developing the functional form of the model. For the same period, the predictions of the model were compared also with simulation results using the default value of reflectivity (0.2). For some days there are no measurements recorded, and as such, those days were excluded from the analysis. The missing days will be specified in the section corresponding

to each period of interest: ground free of snow, snow accumulation and snow melting, respectively.

8.2.1 Ground free of snow

Based on the observations made during the data collection period, the ground was noticed to be free of snow between April and November 2017. The following days were excluded from the analysis: May 23 and 24, July 4 to 16, 27 and 31, August 16 and 17, as well as November 2, 3, 16, 20, and 28.

Using the predictions of the new model, and the default value of reflectivity (0.2), simulations with 10 minutes time-step were performed for each month of the ground free of snow period. The predicted values were reported each hour as in the following example: 11:05, 11:15, 11:25, 11:35, 11:45, and 11:55. The values of solar irradiance predicted by the model and the measured values were averaged hourly (around the 11:05 time for example), and plotted over time, to compare the two trends. Appendix G presents sample graphs of averaged hourly predicted and measured solar irradiance versus time for each period. The values predicted using the default reflectivity 0.2 were also averaged as previously explained and compared with the measured data. Figures 39 and 40 illustrate the comparison of hourly averaged predicted solar irradiance using the default reflectivity, and the reflectivity predicted by the model with hourly averaged measured data, for two representative days: one day with overcast/mixed sky (global horizontal irradiance smaller than 200 W/m^2 , and one day with clear sky (global horizontal irradiance higher than 400 W/m^2).

The difference between the hourly averaged predicted and measured values was calculated for each day. Further, the total difference for a day, and for the whole month

was found adding the hourly values, and the daily values, respectively.

Figure 39. Comparison between the hourly averaged predicted and measured solar irradiance for a day with overcast/mixed sky (ground free of snow)

Figure 40. Comparison between the hourly averaged predicted and measured solar irradiance for a day with clear sky (ground free of snow)

Table 5 presents the daily difference between the predicted (using the reflectivity predicted by the new model and using the default reflectivity) and measured incident solar irradiance for three months of the ground free of snow period: April, June, and November. Descriptive statistics of the difference between the predicted and measured values corresponding to each month of the period are presented in Appendix H.

Table 5. Difference between the predicted and measured solar irradiance incident on a south oriented surface for each day and for April, June, and November (ground free of snow)

Day of month	Difference between model prediction and measured values [MJ/m ² /day]			Difference between default reflectivity (0.2) and measured values [MJ/m ² /day]		
	Apr.	June	Nov.	Apr.	June	Nov.
1	0.01	-0.28	-0.26	0.07	-0.07	-0.07
2	2.65	0.22	0.00	2.65	0.22	0.22
3	1.35	0.43	0.00	1.32	0.65	0.65
4	0.19	0.07	-0.91	0.21	0.14	0.14
5	1.76	0.14	-0.05	1.84	0.21	0.21
6	0.21	0.37	0.11	0.24	0.47	0.47
7	1.11	1.17	-0.74	1.17	1.39	1.39
8	2.33	0.53	0.69	2.32	0.75	0.75
9	-0.87	1.69	0.84	-0.88	1.93	1.93
10	1.31	0.61	-0.77	1.36	0.84	0.84
11	0.67	1.11	-1.38	0.75	1.34	1.34
12	1.22	0.48	0.26	1.30	0.68	0.68
13	1.55	1.36	-0.18	1.55	1.57	1.57
14	1.89	1.48	-0.19	1.89	1.70	1.70
15	-1.18	-0.68	-1.22	-1.20	-0.51	-0.51
16	0.41	0.55	0.00	0.43	0.66	0.66
17	-0.08	1.37	-0.17	-0.03	1.56	1.56
18	1.71	1.25	-0.28	1.73	1.47	1.47
19	0.09	0.65	-0.53	0.10	0.89	0.89
20	1.38	0.72	0.00	1.51	0.97	0.97
21	1.11	2.12	-0.75	1.20	2.41	2.41
22	1.77	-0.34	0.06	1.90	-0.16	-0.16
23	1.05	0.70	-0.58	1.13	0.88	0.88
24	0.88	1.94	0.70	0.96	2.22	2.22
25	-1.04	0.85	-0.10	-1.02	0.96	0.96
26	2.65	0.59	-1.03	2.83	0.80	0.80
27	3.50	0.63	0.03	3.68	0.80	0.80
28	2.13	0.93	0.00	2.24	1.18	1.18
29	3.01	0.33	0.60	3.15	0.41	0.41
30	-1.11	0.48	-1.85	-1.05	0.57	0.57

Based on the values of difference between the predicted and measured values for each day, the daily average difference, and the difference for the whole month were calculated for both cases: reflectivity predicted by the new model and default reflectivity. Table 6 presents the daily average difference and the difference for the whole month for the ground free of snow period.

Table 6. Daily average difference between the predicted and measured values, and monthly difference for the ground free of snow period

Month	Apr.	May	June	July	Aug.	Sept.	Oct.	Nov.
Daily average difference model [MJ/m ² /day]	1.1	0.8	0.7	1.0	1.0	1.3	1.2	-0.3
Daily average difference default [MJ/m ² /day]	1.1	1.8	0.9	1.4	2.2	1.3	1.1	0.8
Monthly difference model [MJ/m ² /month]	31.7	22.4	21.5	20.6	28.5	39.3	35.9	-7.7
Monthly difference default [MJ/m ² /month]	33.4	50.9	26.9	28.1	62.2	38.5	33.8	19.5

8.2.2 Snow accumulation

Based on the observations made during the data collection period, the snow accumulation period was noticed to be from January, February and December 2017. The following days were excluded from the analysis: December 23 to 31, January 1 to 5, 10, 20, 21, 22, 23, and February 15 and 16.

As in the previous case, using the default value of reflectivity (0.2), and the predictions of the new model, simulations with 10 minutes time-step were run for each month of the period. The values of hourly averaged predicted solar irradiance for each month, calculated as in the previous case, were plotted over time, to compare the two trends with hourly averaged measured data. Figures 41 and 42 illustrate the comparison of hourly averaged predicted solar irradiance using the default reflectivity, and the reflectivity predicted by the

model with hourly averaged measured data, for two representative days: one day with overcast sky (global horizontal irradiance smaller than 150 W/m^2 , and one day with clear sky (global horizontal irradiance higher than 400 W/m^2).

Figure 41. Comparison between the hourly averaged predicted and measured solar irradiance for a day with overcast sky (snow accumulation)

Figure 42. Comparison between the hourly averaged predicted and the measured solar irradiance for a day with clear sky (snow accumulation)

The difference between the hourly averaged predicted and measured values was calculated for each day. Further, the total difference for each day, and for the whole month was found adding the hourly values, and the daily values, respectively.

Table 7 presents the average difference between the predicted incident solar irradiance and the measured one for each representative day, and for the whole month.

Table 7. Difference between the predicted and measured solar irradiance incident on a south oriented surface for each day and for January, February, and December (snow accumulation)

Day of month	Difference between model prediction and measured values [MJ/m ² /day]			Difference between default reflectivity (0.2) and measured values [MJ/m ² /day]		
	Jan.	Feb.	Dec.	Jan.	Feb.	Dec.
1	-	-0.46	0.90	-	-1.34	1.01
2	-	-1.02	0.78	-	-2.04	0.82
3	-	0.32	1.85	-	-2.55	2.02
4	-	0.46	2.04	-	-0.12	1.98
5	-	-0.18	0.39	-	-0.42	0.38
6	2.68	0.71	1.64	-1.07	-1.48	3.56
7	1.45	-0.40	1.63	-0.36	-0.71	1.10
8	0.69	-1.21	3.56	-0.46	-2.44	2.81
9	0.72	-0.19	1.73	-0.76	-1.79	0.93
10	-	-1.24	0.85	-	-3.21	0.74
11	0.15	-0.69	1.37	0.01	-0.70	-1.46
12	-0.18	-0.55	0.44	-0.20	-0.56	-0.16
13	2.69	-0.40	0.73	-0.24	-1.41	-1.12
14	0.87	0.77	0.97	-0.07	-0.72	-1.88
15	-0.64	-	1.27	-1.83	-	-0.62
16	0.98	-	0.55	-0.79	-	-0.08
17	-0.29	-1.55	1.61	-0.50	-3.38	-0.17
18	-0.17	-2.10	0.26	-0.28	-2.28	-0.23
19	-0.20	-2.61	0.08	-0.23	-2.76	0.06
20	1.73	0.56	3.59	-1.71	-2.22	-2.06
21	3.71	1.08	3.22	-3.47	-0.31	-1.21
22	-	-0.18	0.39	-	-0.20	0.24
23	-	0.43	0.67	-	0.39	-0.65
24	-0.5	0.22	-	-0.59	0.19	-
25	-1.04	0.03	-	-1.40	-0.10	-
26	-0.38	3.75	-	-0.57	-0.15	-
27	0.42	0.43	-	-0.64	1.32	-
28	-0.23	0.73	-	-0.56	1.18	-
29	-0.12	0.33	-	-0.48	0.41	-
30	0.45	0.48	-	-1.65	0.57	-

Based on the values of difference between the predicted and measured values for each day, the daily average difference, and the difference for the whole month were calculated for both cases: reflectivity predicted by the new model and default reflectivity. Table 8 presents the daily average difference and the difference for the whole month for the ground free of snow period.

Table 8. Daily average difference between the predicted and measured values, and monthly difference for the snow accumulation period

Month	Jan.	Feb.	Dec.
Daily average difference model [MJ/m ² /day]	0.56	-0.09	1.33
Daily average difference default [MJ/m ² /day]	-0.81	-0.96	0.26
Monthly difference model [MJ/m ² /month]	12.3	-2.48	1.28
Monthly difference default [MJ/m ² /month]	-17.8	-26.8	0.16

8.2.3 Snow melting

Based on the observations made during the data collection period, the snow melting period was noticed to be mostly during March 2017.

As for the previous two periods, using the default value of reflectivity (0.2), and the predictions of the new model, a simulation with 10 minutes time-step was run for March. The values of hourly averaged predicted solar irradiance were plotted over time, to compare the two trends with hourly averaged measured data, as in the previous case. Figures 43 and 44 illustrate the comparison of hourly averaged predicted solar irradiance using the default reflectivity, and the reflectivity predicted by the model with hourly averaged measured data, for two representative days: one day with overcast sky (global horizontal irradiance smaller than 200 W/m², and one day with clear sky (global horizontal irradiance higher than 400 W/m²).

Figure 43. Comparison between the hourly averaged predicted and measured solar irradiance for a day with overcast sky (snow melting)

Figure 44. Comparison between the hourly averaged predicted and measured solar irradiance for a day with clear sky (snow melting)

The difference between the hourly averaged predicted and measured values was calculated for each day. Further, the total difference for a day, and for the whole month was found adding the hourly values, and the daily values, respectively.

Table 9 presents the average difference between the predicted incident solar irradiance and the measured one for each day, and for the whole month.

Table 9. Difference between the predicted and measured solar irradiance incident on a south oriented surface for each day and for March (snow melting)

Day of month	Difference between model prediction and measured values [MJ/m ² /day]	Difference between default reflectivity (0.2) and measured values [MJ/m ² /day]
	March	March
1	-0.02	-0.04
2	0.09	0.09
3	2.49	2.84
4	0.43	-1.82
5	0.77	0.40
6	1.45	0.09
7	-0.05	-0.06
8	1.21	1.47
9	1.78	1.90
10	0.44	0.43
11	0.23	0.36
12	0.81	0.11
13	0.77	-0.62
14	-0.29	-0.69
15	-1.20	-1.46
16	-1.12	-1.50
17	0.85	-2.79
18	1.33	-1.63
19	-0.40	0.22
20	0.17	0.54
21	2.33	2.33
22	1.02	1.43
23	1.04	1.69
24	-1.08	-1.31
25	-2.26	-3.29
26	-0.48	-2.77
27	-0.50	-0.50
28	0.53	0.59
29	2.44	3.44
30	1.08	1.57

Based on the values of difference between the predicted and measured values for each day, the daily average difference, and the difference for the whole month were calculated for both cases: reflectivity predicted by the new model and default reflectivity. Table 10 presents the daily average difference and the difference for the whole month for the ground free of snow period.

Table 10. Daily average difference between the predicted and measured values, and monthly difference for the snow melting period

Month	March
Daily average difference model [MJ/m ² /day]	0.46
Daily average difference default [MJ/m ² /day]	0.03
Monthly difference model [MJ/m ² /month]	13.8
Monthly difference default [MJ/m ² /month]	1.04

Descriptive statistics of the difference between the predictions of the model and the measured data for each period are presented in Appendix G.

8.3 Estimation of solar irradiance incident on a 60° sloped surface

As in the case of a south oriented façade, the predictions of the model were compared with measured values of incident solar irradiance, for the period January-December 2017. The predictions of the model were compared also with simulation results using the default reflectivity (0.2). The days excluded from the analysis are the same as in the case of the south oriented facade.

8.3.1 Ground free of snow

Similar with the case of the south oriented façade, using the predictions of the new model, and the default value of reflectivity (0.2), simulations with 10 minutes time-step were

performed for each month of the ground free of snow period. The values of hourly averaged solar irradiance predicted by the model and the hourly averaged measured values were plotted over time, to compare the two trends. Appendix G presents sample graphs of hourly averaged predicted and measured solar irradiance versus time for each period. The hourly averaged values predicted using the default reflectivity 0.2 were also compared with the hourly averaged measured data. Figures 45 and 46 illustrate the comparison of hourly averaged predicted solar irradiance using the default reflectivity, and the reflectivity predicted by the model with hourly averaged measured data, for two representative days: one day with overcast/mixed sky (global horizontal irradiance smaller than 200 W/m^2 , and one day with clear sky (global horizontal irradiance higher than 400 W/m^2).

Figure 45. Comparison between the hourly averaged predicted and measured solar irradiance for a day with overcast sky (ground free of snow)

Figure 46. Comparison between the hourly averaged predicted and measured solar irradiance for a day with clear sky (ground free of snow)

The difference between the hourly averaged predicted (using the new model and using the default reflectivity) and hourly averaged measured incident solar irradiance was calculated every day for the whole ground free of snow period. Table 11 presents these values for April, June, and November.

Based on the difference between the hourly averaged predicted and measured values for each day, the daily average difference, and the difference for the whole month were calculated for both cases: reflectivity predicted by the new model and default reflectivity. Table 12 presents the daily average difference and the difference for the whole month for the ground free of snow period.

Descriptive statistics of the difference between the predicted and measured values corresponding to each month of the period are presented in Appendix H.

Table 11. Difference between the predicted and measured solar irradiance incident on a 60°-tilted surface for each day and for the month of April (ground free of snow)

Day of month	Difference between model prediction and measured values [MJ/m ² /day]			Difference between default reflectivity (0.2) and measured values [MJ/m ² /day]		
	Apr.	June	Nov.	Apr.	June	Nov.
1	0.02	-1.12	0.36	0.05	-1.01	0.35
2	0.71	-0.04	0.17	0.71	-0.04	0.00
3	-0.53	0.06	1.29	-0.55	0.18	0.00
4	0.04	-0.64	0.78	0.05	-0.60	0.73
5	1.09	-0.15	0.13	1.13	-0.11	0.12
6	0.01	0.10	0.90	0.03	0.15	0.88
7	0.54	-0.61	1.70	0.57	-0.49	1.62
8	0.41	-1.34	1.09	0.40	-1.22	1.04
9	-2.50	1.44	0.64	-2.50	1.56	0.62
10	0.05	-1.60	1.53	0.08	-1.48	1.43
11	0.28	-0.42	1.48	0.32	-0.30	1.39
12	0.63	-0.86	1.38	0.68	-0.75	1.32
13	-0.59	1.10	0.39	-0.59	1.21	0.38
14	-0.11	-0.35	0.40	-0.11	-0.23	0.39
15	-2.38	-2.93	1.11	-2.38	-2.84	1.04
16	0.16	0.03	0.45	0.18	0.09	0.00
17	-0.87	0.85	1.36	-0.84	0.95	1.27
18	-0.32	0.24	0.27	-0.31	0.36	0.27
19	-0.08	-0.33	0.69	-0.08	-0.20	0.67
20	0.72	-0.57	1.04	0.79	-0.43	0.00
21	1.09	1.71	0.76	1.14	1.87	0.73
22	1.59	-2.13	0.70	1.66	-2.03	0.67
23	-0.93	0.05	0.45	-0.89	0.15	0.44
24	-1.16	-0.33	0.82	-1.12	-0.18	0.78
25	-2.16	-0.24	0.22	-2.14	-0.19	0.22
26	1.84	-2.03	0.83	1.93	-1.93	0.78
27	2.47	-0.58	1.90	2.57	-0.49	0.97
28	0.88	0.26	0.97	0.94	0.40	0.00
29	1.94	-0.05	0.87	2.02	-0.01	0.82
30	1.58	0.18	0.88	1.61	0.23	0.87

Table 12. Daily average difference between the predicted and measured values, and monthly difference for the ground free of snow period

Month	Apr.	May	June	July	Aug.	Sept.	Oct.	Nov.
Daily average difference model [MJ/m ² /day]	0.1	0.1	-0.3	0.2	-0.1	-0.1	0.2	0.9
Daily average difference default [MJ/m ² /day]	0.2	0.2	-0.2	0.6	0.0	-0.1	0.1	0.8
Monthly difference Model [MJ/m ² /month]	4.4	2.9	-10.3	3.2	-2.5	-2.4	5.3	21.7
Monthly difference default [MJ/m ² /month]	5.3	5.0	-7.4	12.0	-1.0	-2.8	4.1	19.8

8.3.2 Snow accumulation

As in the previous case, using the default value of reflectivity (0.2), and the predictions of the new model, simulations with 10 minutes time-step were run for each month of the period. The values of hourly averaged solar irradiance for each month were plotted over time, to compare the two trends with hourly averaged measured data. Figures 47 and 48 illustrate the comparison of hourly averaged predicted solar irradiance using the default reflectivity, and the reflectivity predicted by the model with hourly averaged measured data, for two representative days: one day with overcast sky (global horizontal irradiance smaller than 200 W/m², and one day with clear sky (global horizontal irradiance higher than 400 W/m²).

The daily difference between the predicted (using the reflectivity predicted by the new model and using the default reflectivity) and measured incident solar irradiance was calculated for the three months of the snow accumulation period: January, February, and December. These values are presented further, in Table 13.

Figure 47. Comparison between the hourly averaged predicted and measured solar irradiance for a day with overcast sky (snow accumulation)

Figure 48. Comparison between the hourly averaged predicted and measured solar irradiance for a day with clear sky (snow accumulation)

Table 13 presents the daily difference between the predicted (using the reflectivity predicted by the new model and using the default reflectivity) and measured incident solar irradiance.

Table 13. Difference between the predicted and measured solar irradiance incident on 60°-tilted surface for each day and for January, February, and December (snow accumulation)

Day of month	Difference between model prediction and measured values [MJ/m ² /day]			Difference between default reflectivity (0.2) and measured values [MJ/m ² /day]		
	Jan.	Feb.	Dec.	Jan.	Feb.	Dec.
1	-	0.29	0.59	-	-0.18	0.72
2	-	-0.35	0.49	-	-0.91	0.54
3	-	0.70	1.45	-	-0.85	1.41
4	-	0.61	1.53	-	0.30	1.49
5	-	0.01	0.36	-	-0.01	0.36
6	1.64	0.63	0.53	-1.41	-0.55	2.65
7	0.00	-0.14	1.12	-0.59	-0.30	0.83
8	1.05	0.08	2.45	-0.93	-0.58	2.04
9	1.17	0.65	1.10	-0.21	-0.28	0.67
10	-	-0.18	1.11	-	-1.24	1.05
11	0.88	-0.39	1.49	-0.81	-0.40	-1.43
12	0.29	-0.33	0.50	-0.28	-0.33	-0.48
13	2.45	0.12	1.50	-1.13	-0.47	-1.23
14	1.59	1.81	1.30	-1.16	-1.18	-0.79
15	-0.34	-	1.15	-0.98	-	-0.80
16	1.24	-	1.61	-1.14	-	-1.35
17	1.05	-0.61	3.27	-0.94	-1.60	-2.50
18	0.17	-0.65	0.35	0.16	-0.76	-0.34
19	0.54	-1.09	0.23	-0.52	-1.17	0.22
20	2.14	1.01	3.20	-2.13	-0.49	-2.37
21	4.12	0.99	2.82	-3.98	0.24	1.74
22	-	0.13	0.50	-	0.12	0.42
23	-	0.66	0.90	-	0.64	0.90
24	0.01	0.17	-	-0.04	0.15	-
25	-0.20	-0.06	-	-0.24	-0.13	-
26	0.57	1.89	-	-0.46	-0.21	-
27	1.07	1.09	-	-0.50	1.03	-
28	0.35	0.26	-	0.34	0.40	-
29	1.05		-	-1.02		-
30	1.94		-	-0.81		-

Based on the difference between the hourly averaged predicted and measured values, the daily average difference, and the difference for the whole month were calculated for both cases: reflectivity predicted by the new model and default reflectivity. Table 14 presents the daily average difference and the difference for the whole month for the snow accumulation period.

Table 14. Daily average difference between the predicted and measured values, and monthly difference for the snow accumulation period

Month	Jan.	Feb.	Dec.
Daily average difference model [MJ/m ² /day]	1.04	0.28	1.28
Daily average difference default [MJ/m ² /day]	-0.85	-0.34	0.16
Monthly difference model [MJ/m ² /month]	22.8	7.30	29.5
Monthly difference default [MJ/m ² /month]	-18.8	-8.76	3.75

Descriptive statistics of the difference between the predicted and measured values corresponding to each month of the period are presented in Appendix H.

8.3.3 Snow melting

As for the previous two periods, using the default value of reflectivity (0.2), and the predictions of the new model, a simulation with 10 minutes time-step was run for March. The values of hourly averaged solar irradiance were plotted over time, to compare the two trends with hourly averaged measured data. Figures 49 and 50 illustrate the comparison of hourly averaged predicted solar irradiance using the default reflectivity, and the reflectivity predicted by the model with hourly measured data, for two representative days: one day with overcast sky (global horizontal irradiance smaller than 200 W/m², and one day with clear sky (global horizontal irradiance higher than 400 W/m²).

Figure 49. Comparison between the predicted solar irradiance and the measured one for a day with overcast sky (snow melting)

Figure 50. Comparison between the predicted solar irradiance and the measured one for a day with clear sky (snow melting)

The daily difference between the predicted (using the reflectivity predicted by the new model and using the default reflectivity) and measured incident solar irradiance was calculated for the snow melting period too. These values are presented further, in Table 15.

Table 15. Difference between the predicted and measured solar irradiance incident on a 60°-tilted surface for each day and for March (snow melting)

Day of month	Difference between model prediction and measured values [MJ/m ² /day]	Difference between default reflectivity (0.2) and measured values [MJ/m ² /day]
	March	March
1	-0.17	-0.20
2	0.03	0.03
3	1.16	3.31
4	0.88	-2.34
5	1.12	-0.39
6	0.59	-0.14
7	-0.13	-0.13
8	0.33	0.36
9	0.15	0.64
10	1.43	-0.29
11	1.10	-0.70
12	0.41	-1.19
13	0.18	-1.50
14	-0.26	-0.51
15	-0.63	-0.77
16	-1.44	-1.63
17	0.93	-1.68
18	0.66	-1.72
19	-0.36	-0.75
20	-0.36	-0.40
21	1.17	1.17
22	1.19	-0.67
23	0.42	-0.44
24	-0.54	-0.66
25	0.76	0.75
26	-0.67	-1.90
27	-0.38	-0.38
28	0.00	0.03
29	2.10	2.09
30	-0.02	-0.29

Based on the values of difference between the hourly averaged predicted and measured values, the daily average difference, and the difference for the whole month were calculated for both cases: reflectivity predicted by the new model and default reflectivity. These values are presented in Table 16.

Table 16. Daily average difference between the predicted and measured values, and monthly difference for the snow melting period

Month	March
Daily average difference model [MJ/m ² /day]	0.32
Daily average difference default [MJ/m ² /day]	-0.34
Monthly difference model [MJ/m ² /month]	9.65
Monthly difference default [MJ/m ² /month]	-10.3

Descriptive statistics of the difference between the predictions of the model and the measured data for each period are presented in Appendix G.

8.4 Results analysis

Sections 8.2 and 8.3 present the predicted solar irradiance incident on a south oriented façade and on a 60°-sloped surface, using the default reflectivity of ESP-r (0.2) and the reflectivity predicted by the new model. The analysis of these results will be performed in the following sections.

8.4.1 Solar irradiance incident on the south façade

Ground free of snow period

Analysing the graphs of predicted and measured solar irradiance versus time (sample presented in Appendix G) for both cases: default reflectivity and reflectivity predicted by the model was noticed that the model alternates between over and under predicting the

solar irradiance for all types of cloud cover. Moreover, it was noticed that for most days, the overprediction is more significant in the afternoon. According to Figure 39 (page 103), presenting the predicted and measured solar irradiance for a day with overcast/mixed sky, the difference between the predictions of the model and those of default reflectivity are almost unnoticeable even though the new model is overpredicting the reflectivity. On the other hand, as Figure 40 (page 103) illustrates, for a day with clear sky, the difference between the predictions of the new model and those of default reflectivity are more noticeable around noon. It can be also noticed that the values of solar irradiance predicted by the model are closer to the measured values than the ones predicted by the default reflectivity. Observations made during the data collection period led to the conclusion that for the ground free of snow season, around noon, the reflectivity is very frequently smaller than 0.2. However, for both types of day, the predictions of the new model are close to the predictions of the solar irradiance using the default value of reflectivity.

According to Table 6 (page 105), the monthly values of solar irradiance provided by the new model are closer to the measured ones than the values predicted using the default reflectivity for all months of the ground free of snow period, excepting September. The difference between the predictions of the model and those using the default reflectivity is larger for May, June, July, and August, when the reflectivity registers frequently values lower than 0.2 close to noon. For September, the monthly prediction of solar irradiance is slightly closer to the measured one in the case of default reflectivity, while for November both predictions are under estimating the solar irradiance, the default reflectivity more than the new model. According to the observations made during the data collection period, for May the measured average reflectivity was 0.235, due to the freshly grown grass, while for

November, the measured average reflectivity was 0.284, partly due to the presence of frost on grass for some days, and partly due to higher values of the solar zenith angle close to noon compared with the summer.

For the whole ground free of snow period, the difference between the predictions of the new model and the measured values was found to be 192 MJ/m^2 , while the difference between the predictions of default reflectivity and the measured values was 263 MJ/m^2 . Even though the difference between these two predictions is only 71 MJ/m^2 , the new model is improving the prediction of solar irradiance incident on a south oriented façade.

Snow accumulation period

Analysing the variation of predicted and measured solar irradiance versus time (sample graphs presented in Appendix G) for both cases: default reflectivity and reflectivity predicted by the model was noticed that as in the previous case, the model alternates between over and under predicting the solar irradiance for all types of cloud cover. Similar with the ground free of snow period, it was noticed that for most days, the overprediction is more significant in the afternoon. According to Figures 41 and 42 (page 106), presenting the predicted and measured solar irradiance for a day with overcast/mixed sky, and for a day with clear sky, respectively, the difference between predictions and measured values is noticeable for both days. It can be also noticed that the solar irradiance predicted by the new model is closer to the measured one. For the snow accumulation period, for most days, the reflectivity has values around 0.8, significantly higher than 0.2, the default value of reflectivity, leading to noticeable difference in predictions for all types of sky.

According to Tables 7 and 8 (page 107, 108), it can be also noticed that most of the time the default reflectivity provides predictions smaller than the measured values (some

predictions are slightly higher for days when snow is not present on ground). The difference between the predictions of the model and those using the default reflectivity is larger for January and February, when the snow was present on ground for most days. For December, when almost half of the month was no snow on the ground, the difference is smaller.

Higher difference between the predicted values using the new model and the measured values was noticed for days with freezing rain. In these cases, the model detects the presence of snow, increasing thus the reflectivity, while the reflectivity decreases due to the metamorphic processes snow experiences (coalescence of particles) in the presence of water and below zero temperatures.

For the whole snow accumulation period, the new model is overpredicting the solar irradiance with 11 MJ/m^2 , while the default reflectivity is underpredicting the solar irradiance with 44 MJ/m^2 . Even though the difference between the predicted and measured values is relatively small, the new model provides predictions closer to the measured data than the default reflectivity.

Snow melting period

As in the previous two cases, analysing the graphs of predicted and measured solar irradiance versus time (sample presented in Appendix G) for both cases: default reflectivity and reflectivity predicted by the model can be noticed that the model alternates between over and under predicting the solar irradiance. Similar with the ground free of snow and snow accumulation periods, it was noticed that for most days, the overprediction is more significant in the afternoon. According to Figures 43 and 44 (page 109), presenting the predicted and measured solar irradiance for a day with overcast/mixed sky, and for a day

with clear/mixed sky, respectively, the difference between predictions and measured values is more noticeable for days with clear/mixed sky. As Figure 44 (page 109), the difference between the predictions of the new model and the ones of the default reflectivity is more noticeable for the part of the day with clear sky. For the part of the day with intermittent cloudiness the difference is almost unnoticeable even though the predicted reflectivity is higher than the default one (approximately 0.4 compared with 0.2). The sky model used for predicting the solar irradiance on inclined surfaces, as well as the way the system interpolates the values of solar radiation provided by the weather file my account partially for this small difference.

According to Table 9 (page 110), the daily values of solar irradiance provided by the new model are most of the time positive, indicating that the model is overpredicting the solar irradiance. The difference between the predicted and measured values was noticed to be larger for days when the snow cover is no longer continuous, and patches of bare ground alternate with patches of snow. For those days the default reflectivity provides predictions slightly lower than the measured values.

For the whole snow melting period, the new model is overpredicting the solar irradiance with almost 14 MJ/m^2 , while the default reflectivity with just 1 MJ/m^2 . Even though for the whole month the default reflectivity appears to provide better predictions, analysing the daily values of solar irradiance it can be noticed that most of the time the values provided by the new model are closer to the measured values than those provided by the default reflectivity.

8.4.2 Solar irradiance incident on a 60°-sloped surface

Ground free of snow period

As in the case of a south oriented surface, analysing the graphs of predicted and measured solar irradiance versus time (sample presented in Appendix G) for both cases: default reflectivity and reflectivity predicted by the model was noticed that the model alternates again between over and under predicting the solar irradiance for all types of cloud cover.

According to Figure 45 (page 112) and 46 (page 113), presenting the predicted and measured solar irradiance for a day with overcast/mixed sky, and for a day with clear sky, respectively, the difference between predictions and measured values is more noticeable for days with clear sky. As in the case of a vertical surface, for a day with clear sky the difference is more noticeable around noon. However, in the case of a 60°-sloped surface the difference is generally smaller than for a vertical surface.

As Table 10 (page 111) illustrates, the monthly values of solar irradiance provided by the new model are closer to the measured ones than the values predicted using the default reflectivity for April, May, July, while for June, August, October and November, these values are slightly higher than those corresponding to default reflectivity. However, for the whole ground free of snow period, the difference between the predictions of the new model and the measured values is still slightly smaller than the difference between the predictions of default reflectivity and the measured values (23 MJ/m² versus 35 MJ/m²). In this case, the difference between the two predictions is only 12 MJ/m² for the whole eight months period, smaller than the difference corresponding to a vertical surface.

Snow accumulation period

Analysing the graphs of predicted and measured solar irradiance versus time (sample presented in Appendix G) for both cases: default reflectivity and reflectivity predicted by the model was noticed that similar with the case of solar irradiance incident on a vertical south oriented surface, the model alternates between over and under predicting the solar irradiance incident on a 60°-sloped surface for all types of cloud cover. As in the case of ground free of snow period, it was noticed that for most days, the overprediction is more significant in the afternoon. According to Figure 47 and 48 (page 116), presenting the predicted and measured solar irradiance for a day with overcast/mixed sky, and for a day with clear sky, respectively, the difference between predictions and measured values is more noticeable for both days due to significant difference between the predicted and default reflectivity (approximately 0.8 compared with 0.2). As in the case of a vertical surface, the difference is more noticeable around noon, when incoming solar radiation has higher values than in the morning or afternoon. However, as for the ground free of snow period, in the case of a 60°-sloped surface the difference is generally smaller than for a vertical surface.

As Table 14 (page 118) illustrates, it can be noticed that most of the time (January and February) the default reflectivity provides predictions smaller than the measured values. For December some predictions are slightly higher for days when snow is not present on ground. The difference between the predictions of the model and those using the default reflectivity is larger for January and December than for February.

For the whole snow accumulation period, the new model is overpredicting the solar irradiance with 60 MJ/m^2 , while the default reflectivity is underpredicting the solar irradiance with 24 MJ/m^2 . Even though for the whole month the default reflectivity appears to provide better predictions, analysing the daily values of solar irradiance it can be noticed that most of the time the values provided by the new model are closer to the measured values than those provided by the default reflectivity.

Snow melting period

As in the previous two cases, analysing the graphs of predicted and measured solar irradiance versus time (sample presented in Appendix G) for both cases: default reflectivity and reflectivity predicted by the model can be noticed that the model alternates between over and under predicting the solar irradiance. Similar with the ground free of snow and snow accumulation periods, it was noticed that for most days, the overprediction is more significant in the afternoon. According to Figures 49 and 50 (page 119), presenting the predicted and measured solar irradiance for a day with overcast/mixed sky, and for a day with clear/mixed sky, respectively, the difference between predictions and measured values is more noticeable for days with clear/mixed sky. As Figure 50 illustrates, the difference between the predictions of the new model and the ones of the default reflectivity is more noticeable for the part of the day with clear sky. For the part of the day with intermittent cloudiness the difference is almost unnoticeable even though the predicted reflectivity is higher than the default one (approximately 0.4 compared with 0.2). As in the case of a vertical surface, the sky model used for predicting the solar irradiance on inclined surfaces, as well as the way the system interpolates the values of solar radiation provided by the weather file may account partially for this small difference.

As Table 15 (page 120) illustrates, the daily values of solar irradiance provided by the new model are most of the time positive, indicating that the model is overpredicting the solar irradiance. The difference between the predicted and measured values was noticed to be larger for days when the snow cover is no longer continuous, and patches of bare ground alternate with patches of snow. For those days the default reflectivity provides predictions slightly lower than the measured values.

For the whole snow melting period, the new model is overpredicting the solar irradiance with almost 10 MJ/m^2 , while the default reflectivity is underpredicting it with 10 MJ/m^2 . As in the previous case, analysing the values of solar irradiance corresponding to individual days, it can be noticed that most of the time the values provided by the new model are closer to the measured values than those provided by the default reflectivity

9 Chapter: Conclusions and recommendations

9.1 Conclusions

Accurate prediction of energy use or solar collectors' performance requires appropriate values of snow/ground reflectivity. Usually, ground reflectivity has no significant variation from one day to another. However, in the case of ground covered with snow, the reflectivity increases significantly, depending on the environment, and it might register important daily and long-term variations. Many times, the energy use peaks also during the winter season, and by taking advantage of the increased fraction of solar radiation while designing new buildings or retrofitting existing ones, the energy use of the built environment can be scaled down.

An algorithm for predicting the reflectivity for both ground free of snow and ground covered with snow was developed based on data measured in Ottawa. The significant change in reflectivity was noticed to be associated with three periods:

- Ground free of snow – no significant variation from one day to another, and daily reflectivity has small variations around the average value of 0.2;
- Non-melting or snow accumulation period – no significant variation from one day to another due to frequent snow falls, and daily reflectivity has small variations around the average value of 0.8;
- Melting period – significant variation from one day to another due to positive ambient temperatures and isolated snowfalls events. The daily reflectivity might register

significant variations, from 0.8 in the morning to 0.25 in the afternoon, for example.

The predictors of the model were found to be the following:

- Ground free of snow: zenith angle and sky transmissivity;
- Snow accumulation: zenith angle, sky transmissivity and snow age;
- Snow melting: sky transmissivity, snow age, and the difference between ambient temperature and a “threshold” temperature generating high snow melting rate.

According to literature, the average value of reflectivity for ground covered with short grass is 0.25. Based on the observations made during the field study, the average reflectivity of ground covered by short grass (April to November) was found to be 0.208 ± 0.012 , and the average reflectivity predicted by the model was 0.204 ± 0.01 . There is a wide range of estimations of ground reflectivity in the presence of snow. Depending on the environment, values range from 0.2 to 0.85. Based on the observations made during the field study, the average snow reflectivity for the accumulation season was found to be 0.843 ± 0.048 , and the average reflectivity predicted by the model was 0.851 ± 0.048 . For the snow melting season, the average snow reflectivity was found to be 0.587 ± 0.033 , and the average reflectivity predicted by the model was 0.612 ± 0.035 .

To evaluate the impact of the new model, two sets of simulations were performed with ESP-r: estimation of the solar irradiance incident on a south-oriented façade and estimation of the solar irradiance incident on a surface with a 60° slope.

The increase in solar irradiance incident on various surfaces was noticed to vary over time. The increase is more significant for February and March, when the ground is still covered with snow and the global horizontal irradiance has values higher than in December and January. The way ESP-r is interpolating the values of the solar radiation provided by

the weather file, as well as the sky model (Perez anisotropic) may partially account for the difference between predictions and measured values.

For the whole year, the difference between the predictions of the new model and the measured values was found to be 261 MJ/m², while the difference between the predictions of default reflectivity and the measured values was 229 MJ/m². Even though the default reflectivity appears to provide better predictions for the whole year, analysing the daily and monthly values of solar irradiance it can be noticed that most of the time the values provided by the new model are closer to the measured values than those provided by the default reflectivity.

The sensor used for measuring the global horizontal and reflected solar radiation was a Kipp and Zonen CMA6 albedometer, which is sensitive to wavelengths of about 0.3 to 3.0 μm . According to the manufacturer [24], this type of sensing element responds to the total power absorbed, and is theoretically nonselective as to the spectral distribution of the radiation. As such, the new model is appropriate also for daylighting studies.

9.2 Recommendations for future work

The depletion of non-renewable energy resources motivated the research community to find solutions for a more sustainable built environment. In this context, the design and construction of houses integrating passive solar features and solar technologies is becoming more relevant worldwide. Proper estimation of solar irradiance incident on surfaces of various orientations is of great importance for both the efficient operation of buildings and the performance of solar technologies. The present study was conducted in Ottawa, using real weather data characteristic for this region. Further research can be conducted to

evaluate the performance of the model for other locations in Ottawa and also for locations in other climatic regions.

Based on the observations made during the data collection period it was noticed that, for Ottawa region, the snow melting occurs mostly in February and March. This observation led to the calculation of the threshold temperature as a function of the day of year. For other climatic regions, where snow melting might occur in December for example, further improvement of the algorithm can be done by exploring the possibility of calculating the threshold temperature as a function of the declination angle rather than day of year.

During the data collection period, it was noticed that for a grass covered surface, the characteristics of the surface are changing with the season when the ground is free of snow, and reflectivity may vary from a value of 0.15 in April, for example, to 0.3 in November. Investigation in more depth can be conducted to evaluate if the influence of the month/season on the prediction of the model is significant, and if the prediction of solar irradiance incident on various surfaces can be improved. Additionally, after assessing the impact of the model, it was noticed that the solar irradiance is overestimated especially in the afternoon. Further investigation can be conducted, in order to assess the potential improvement of the model, using a lower reflectivity in the afternoon compared with the morning.

Global solar radiation is generally measured on a horizontal surface, whereas the maximum amount of incident solar radiation is measured on an inclined surface. To increase the amount of incident solar radiation on solar panels, they are usually mounted on tilted surfaces. The present study was conducted using the default model of ESP-r for

predicting solar radiation on inclined surfaces (the Perez anisotropic model). Using the other models implemented in ESP-r for predicting the solar radiation on inclined surfaces (Klucher and Muneer), further research can be conducted to find the most suitable model for the given surfaces and location.

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Appendices

Appendix A: Weather log – sample recordings

- **August 22, 2017**

Start 8:00. Temperature around 6°C in the morning, the highest expected 13°C. Short grass, mix of brown grass from winter and new green grass growing. At 8:00 sunny and reflectivity 0.276. At 9:00 reflectivity 0.241, mixed sky, sunny and light clouds. At 10:00 reflectivity around 0.235 and light white clouds cover almost completely the sky. At 11:00 reflectivity 0.225 and mixed sky (incoming solar radiation with significant variation). At 12:00 reflectivity 0.218, and mostly overcast sky. At 13:00 reflectivity 0.210, and mostly overcast sky. At 14:00 reflectivity 0.201 and overcast sky. At 15:00 reflectivity 0.205 and light rain. At 16:00 reflectivity 0.200, overcast sky and light rain. At 17:00 reflectivity 0.202, still overcast sky and light rain. Stop

- **January 2, 2018**

Start 8:00. Temperature -21°C, real feel -30°C, highest expected -14°C. Overcast sky, 25 cm of snow, snow age 151 hours, and reflectivity 0.777. Difference between the recordings of the albedometer and the devices on the roof. At 8:30 the device is stabilized, light snow, very small flakes, like a powder, dry snow, and reflectivity 0.838. At 9:00 still overcast, light snow, and reflectivity 0.842. At 10:00 overcast sky, still snowing, small flakes, and reflectivity 0.851. At 11:00 overcast and still snowing, reflectivity 0.873. At 12:00 still overcast sky, snowing (light to moderate) and reflectivity 0.893. At 13:00 still overcast, snow stopped, approximately 5 cm of fresh snow on top of the old one, reflectivity 0.887.

At 14:00 still overcast and reflectivity 0.889. At 15:00 overcast and reflectivity 0.887. At 16:00 overcast and reflectivity 0.888. Stop at 16:30.

- **March 23**

Start 7:00. Temperature -2°C in the morning, highest expected in the afternoon 5°C . Mostly overcast sky, not very dark clouds, snow depth 5 cm, age around 200 hours, reflectivity 0.785 (stabilization, difference between the albedometer and the devices on the roof 10 W/m^2), $T=-1.6152^{\circ}\text{C}$, RH 0.4948. At 7:30 clear sky with a few white clouds, some of them covering the sun, reflectivity 0.675, $T=-1.7319^{\circ}\text{C}$, RH 0.4997. At 8:00 mixed sky with white clouds, some of them covering the sun, reflectivity 0.650, $T = -1.8108^{\circ}\text{C}$, RH 0.5017. At 9:00 mostly overcast, reflectivity 0.643, $T=-1.4647^{\circ}\text{C}$, RH 0.4977. At 10:00 still overcast, reflectivity 0.637, $T=-1.0251^{\circ}\text{C}$, RH 0.4857. At 11:00 mostly overcast, reflectivity 0.626, $T=-0.4047^{\circ}\text{C}$, RH 0.4771. At 12:00 mixed sky, reflectivity 0.618, $T=1.4647^{\circ}\text{C}$, RH 0.4977. At 13:00 mostly sunny, some white clouds on the sky, reflectivity 0.612, temp = 3.6244, RH 0.3416. At 14:00 mostly sunny, some white clouds on the sky, reflectivity 0.594, temp = 4.5473, RH 0.3416. At 15:00 mostly sunny, some white clouds on the sky, reflectivity 0.583, temp = 4.9860, RH 0.3369. At 17:00 mostly sunny, some white clouds on the sky, reflectivity 0.574, temp = 5.4061, RH 0.3218. At 18:00 mixed sky, white clouds, reflectivity 0.545, temp 5.4868, RH=0.3224. Stop 18:30

Appendix B: Measurement uncertainty calculation

The most common method used to describe data acquisition system accuracy is to compute the root-sum squared (RSS) errors of the system components. The RSS error is a statistical value which is equivalent to the standard deviation (1σ), and represents the square root of the sum of the squares of the peak errors of each component.

$$\varepsilon = \sqrt{\varepsilon_1^2 + \varepsilon_2^2 + \dots + \varepsilon_n^2}$$

According to Kipp and Zonen, the CMA6 albedometer is subject to the following types of errors:

- Non-stability error, $\varepsilon_1 = 1\%$;
- Non-linearity error, $\varepsilon_2 = 1\%$;
- Temperature error, $\varepsilon_3 = 4\%$;
- Tilt response error, $\varepsilon_4 = 1\%$.

The total error of the albedometer, ε_A is the following:

$$\varepsilon_A = \sqrt{\varepsilon_1^2 + \varepsilon_2^2 + \varepsilon_3^2 + \varepsilon_4^2} = 4.35\%$$

The National Instruments CFP 2220 data logger has the offset error $\varepsilon_{01}=5.72\%$, while the PXI 1078 data logger has the offset error $\varepsilon_{02}=3.65\%$.

The measurement uncertainty of the system albedometer-data logger is the following:

- CFP 2220 data logger: $\varepsilon = \sqrt{\varepsilon_A^2 + \varepsilon_{01}^2} = 8.40\%$
- PXI 1078 data logger: $\varepsilon = \sqrt{\varepsilon_A^2 + \varepsilon_{02}^2} = 5.70\%$

Appendix C: Ordinary least square and robust fit methods

Ordinary least squares method

The *Data Analysis, Multiple Regression* tool of Microsoft Excel and *fitlm* function of Matlab use the method of ordinary least squares when fitting data. Fitting requires a parametric model that relates the response data to the predictor data with one or more coefficients. The result of the fitting process is an estimate of the model coefficients.

To obtain the coefficient estimates, the least-squares method minimizes the summed square of residuals. The residual for the i th data point r_i is defined as the difference between the observed response value y_i and the fitted response value $\hat{y}_i$, and is identified as the error associated with the data:

$$r_i = y_i - \hat{y}_i$$

The summed square of residuals is given by:

$$S = \sum_{i=1}^n r_i^2 = \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

where n is the number of data points included in the fit and S is the sum of squares error estimate.

Robust fit method

The main disadvantage of least-squares fitting is its sensitivity to outliers. Outliers have a large influence on the fit because squaring the residuals magnifies the effects of these extreme data points. To minimize the influence of outliers, the data can be fitted using robust least-squares regression. Matlab provides these two robust regression methods:

- Least absolute residuals (LAR) — The LAR method finds a curve that minimizes the absolute difference of the residuals, rather than the squared differences. Therefore, extreme values have a lesser influence on the fit.
- Bisquare weights — This method minimizes a weighted sum of squares, where the weight given to each data point depends on how far the point is from the fitted line. Points near the line get full weight. Points farther from the line get reduced weight. Points that are farther from the line than would be expected by random chance get zero weight.

The bisquare weight method was used because it simultaneously seeks to find a curve that fits the bulk of the data using the usual least-squares approach, and it minimizes the effect of outliers. Robust fitting with bisquare weights uses an iteratively reweighted least-squares algorithm, and follows this procedure:

1. Fit the model by weighted least squares.
2. Compute the adjusted residuals and standardize them. The adjusted residuals are given by:

$$r_{adj} = \frac{r_i}{\sqrt{1 - h_i}}$$

where r_i are the usual least-squares residuals and h_i are leverages that adjust the residuals by reducing the weight of high-leverage data points, which have a large effect on the least-squares fit. The standardized adjusted residuals are given by:

$$u = \frac{r_{adj}}{K_s}$$

where K_s is a tuning constant equal to 4.685, and s is the robust variance given by $MAD/0.6745$ where MAD is the median absolute deviation of the residuals.

3. Compute the robust weights as a function of u . The bisquare weights are given by:

$$w_i = \begin{cases} (1 - (u_i)^2)^2, & |u_i| < 1 \\ 0 & , |u_i| \geq 1 \end{cases}$$

Error Distribution

When fitting data that contains random variations, there are two important assumptions that are usually made about the error:

- The error exists only in the response data, and not in the predictor data.
- The errors are random and follow a normal (Gaussian) distribution with zero mean and constant variance, σ^2 .

The errors are assumed to be normally distributed because the normal distribution often provides an adequate approximation to the distribution of many measured quantities. Although the least-squares fitting method does not assume normally distributed errors when calculating parameter estimates, the method works best for data that does not contain a large number of random errors with extreme values. The normal distribution is one of the probability distributions in which extreme random errors are uncommon. However, statistical results such as confidence and prediction bounds do require normally distributed errors for their validity.

Appendix D: Distribution of observed data

Distribution of observed data for each period

Figure 51. Distribution of observed data for ground free of snow period

Figure 52. Distribution of observed data for snow accumulation period

Figure 53. Distribution of observed data for snow melting period

Appendix E: Descriptive statistics and histograms of residuals

Descriptive statistics of residuals for each period of interest are presented in Table 5.

Table 17. Descriptive statistics of residuals

Statistics	Ground free of snow	Snow accumulation	Snow melting
Mean	-0.0025	0.0151	-0.0041
Standard Error	0.0001	0.0004	0.0011
Median	-0.0029	0.0114	0.0089
Mode	#N/A	#N/A	#N/A
Standard Deviation	0.0150	0.0412	0.0715
Sample Variance	0.0002	0.0017	0.0060
Kurtosis	5.226	3.292	0.6124
Skewness	-0.4625	0.0224	-0.6866
Range	0.2349	0.5602	0.4708
Minimum	-0.1295	-0.3374	-0.2504
Maximum	0.1054	0.2228	0.2204
Count	15811	17352	8403

Figure 54. Histogram of residuals for ground free of snow period

Figure 55. Histogram of residuals for snow accumulation period

Figure 56. Histogram of residuals for snow melting period

Appendix F: Fortran code for implementation in ESP-r

```
CALL MZSANG ! Calculate solar altitude
ISUNUP=1
ZET = 90.-SALT ! Calculate zenith angle
WRITE (71, *) ZET

PI=4.0*ATAN(1.0) ! Define pi
R=PI/180. ! Conversion to radians

QT=QFF+QDF*SIN(SALT*R) ! Global horizontal solar radiation
IF(IRTYP.EQ.1) QT=QDF
WRITE (72, *) QT

C Calculate sky transmissivity

GON=1367.*(1+0.033*COS(0.017214*IDYP))
GO=GON*COS(ZET*R)
STRSM=abs(QT/GO)
IF (STRSM.GE.1) STRSM=0.8
WRITE (73, *) STRSM

C Calculate day and month

IF(groundreflmodel.EQ.2) THEN
  IDYAX=IDYP ! day of year
  IF(IHRF.EQ.1) IDYAX=IDYF ! end of day: use next day
  CALL EDAYR(IDYAX,ID,IM) ! calculate day and month

C Detect the presence of snow and calculate snow age
  IF ( (TP.GT.-30. .AND. TP.LE.-15.) .AND.
&      (HP.GT.50. .AND. HP.LT.75.) ) THEN
    SNOW=.TRUE.
    SA = 0.
    write(77,*) 'A'
  ELSEIF (TP.GT.-15. .AND. TP.LE.1. .AND. HP.GT.75. .AND.
&      HP.LT.98.) THEN
    SNOW=.TRUE.
    SA = 0.
    write(77,*) 'B'
  ELSE
    SNOW=.FALSE.
    IF (TP .LE. 1) THEN
      SA = SA + 1./FLOAT(NTSTEP)
    ELSE
      SA = 0.
    ENDIF
    write(77,*) 'C'
  ENDIF
  write(77,*) NSINC, NTSTEP, TP, HP, SA
```

```

: Calculate threshold temperature (TTHS) for melting period

TTHS = -0.064*IDYP+6.69
IF (TTHS .LT. 0.) THEN
    TTHS = 7.
ENDIF

: Select the functional form of the model depending on season

IF (SA .GE. 2. .AND. TP .LE. -10.) THEN
    groundrefl=0.9-0.03*(1-COS(ZET*R))-0.1*STRSM-0.015*SA/24    !Accumulation season
    write(78,*) 'A'
ELSEIF (SA .GE. 2. .AND. TP.GT.-10. .AND. TP.LT.TTHS) THEN
    groundrefl=0.70-0.085*STRSM-0.012*(TP-TTHS)-0.021*SA/24 !Melting season temperatures below threshold temperature
    IF (groundrefl .LT. 0.3) THEN
        groundrefl=0.145+0.07*(1-COS(ZET*R))+0.04*STRSM
        &      -0.0009*(50-ZET) ! Melting season (when the reflectivity is 0.3 the model switches to no snow functional form
    ENDIF
    write(78,*) 'B'
ELSEIF (SA .GE. 2. .AND. TP .GE. TTHS) THEN
    groundrefl=0.9+0.115*STRSM-0.008*(TP-TTHS)-0.041*SA/24    !Melting season temperatures above threshold temperature
    write(78,*) 'C'
    IF (groundrefl .LT. 0.3) THEN
        groundrefl=0.145+0.07*(1-COS(ZET*R))+0.04*STRSM
        &      -0.0009*(50-ZET) ! Melting season (when the reflectivity is 0.3 the model switches to no snow functional form
    ENDIF
    write(78,*) 'D'

ELSE
    groundrefl=0.145+0.07*(1-COS(ZET*R))+0.04*STRSM
    &      -0.0009*(50-ZET)    ! Ground free of snow season

    write(78,*) 'E'

ENDIF
WRITE (78, *) groundrefl, SA, TP, TTHS
WRITE (79, *) groundrefl

```

Appendix G: Sample graphs of predicted and measured solar irradiance versus time for each period

South oriented façade

Figure 57. Hourly averaged predicted and measured solar irradiance incident on a south oriented façade versus time for the ground free of snow period (June)

Figure 58. Hourly averaged predicted and measured solar irradiance incident on a south oriented façade versus time for the snow accumulation period (January)

Figure 59. Hourly averaged predicted and measured solar irradiance incident on a south oriented façade versus time for the snow melting period (March)

60°-tilted surface

Figure 60. Hourly averaged predicted and measured solar irradiance incident on a 60°-tilted surface versus time for the ground free of snow period (June)

Figure 61. Hourly averaged predicted and measured solar irradiance incident on a 60°-tilted surface versus time for the snow accumulation period (January)

Figure 62. Hourly averaged predicted and measured solar irradiance incident on a 60°-tilted surface versus time for the snow melting period (March)

Appendix H: Descriptive statistics of the difference between the predicted and measured values of solar irradiance for each month

Table 18. Descriptive statistics of the difference between the predicted (reflectivity predicted by the new model) and measured values of solar irradiance for the south oriented surface (no snow season)

Month	Apr.	May	June	July	Aug.	Sept.	Oct.	Nov.
Statistics								
Mean	1.1	0.8	0.7	1.0	1.0	1.3	1.2	-0.3
Standard Error	0.2	0.2	0.1	0.2	0.1	0.1	0.1	0.1
Median	1.2	0.5	0.6	0.3	1.1	1.6	1.3	-0.1
Mode	#N/A	0.0	#N/A	0.0	0.0	#N/A	#N/A	0.0
Standard Deviation	1.2	0.8	0.6	0.8	0.6	0.8	0.8	0.6
Sample Variance	1.5	0.7	0.4	0.7	0.4	0.6	0.6	0.4
Kurtosis	-0.4	1.7	0.1	0.5	-0.2	-0.7	-0.6	0.3
Skewness	-0.2	1.1	0.2	1.1	-0.2	-0.6	0.4	-0.5
Range	4.7	4.0	2.8	3.1	2.6	2.8	2.8	2.7
Minimum	-1.2	-0.7	-0.7	-0.1	-0.3	-0.3	0.1	-1.9
Maximum	3.5	3.3	2.1	3.0	2.3	2.5	3.0	0.8
Sum	31.7	22.4	21.5	20.6	28.5	39.3	35.9	-7.7
Count	30	28	30	21	28	30	30	25
Confidence Level of the mean (95.0%)	0.5	0.3	0.2	0.3	0.2	0.3	0.3	0.2

Table 19. Descriptive statistics of the difference between the predicted (default reflectivity) and measured values of solar irradiance for the south oriented surface (no snow season)

Month	Apr.	May	June	July	Aug.	Sept.	Oct.	Nov.
Statistics								
Mean	1.1	1.8	0.9	1.4	2.2	1.3	1.1	0.8
Standard Error	0.2	0.6	0.1	0.2	0.1	0.1	0.1	0.7
Median	1.2	0.9	0.8	0.6	1.2	1.6	1.3	-0.2
Mode	#N/A	#N/A	#N/A	0.0	0.0	#N/A	#N/A	#N/A
Standard Deviation	1.3	3.0	0.7	1.1	0.6	0.7	0.7	3.8
Sample Variance	1.6	9.1	0.5	1.2	0.4	0.6	0.5	14.8
Kurtosis	-0.4	10.0	-0.1	1.7	-0.3	-0.6	-0.5	11.8
Skewness	-0.1	3.2	0.2	1.3	-0.3	-0.6	0.4	3.5
Range	4.9	13.5	2.9	4.2	2.5	2.8	2.8	17.9
Minimum	-1.2	-0.7	-0.5	0.0	-0.2	-0.3	0.0	-1.9
Maximum	3.7	12.9	2.4	4.2	2.4	2.5	2.9	16.0
Sum	33.4	50.9	26.9	28.1	31.3	38.5	33.8	19.5
Count	30	28	30	21	28	30	30	25
Confidence Level of the mean (95.0%)	0.5	1.1	0.3	0.4	0.2	0.3	0.3	1.4

Table 20. Descriptive statistics of the difference between the predicted (reflectivity predicted by the new model) and measured values of solar irradiance for the 60°-sloped surface (no snow season)

Statistics	Month	Apr.	May	June	July	Aug.	Sept.	Oct.	Nov.
Mean		0.1	0.1	-0.3	0.2	-0.1	-0.1	0.2	0.9
Standard Error		0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1
Median		0.1	0.0	-0.3	0.0	-0.1	0.0	0.0	0.7
Mode		#N/A	0.0	#N/A	0.0	0.0	#N/A	#N/A	0.0
Standard Deviation		1.2	0.8	1.0	1.0	0.7	0.7	0.7	0.5
Sample Variance		1.5	0.7	1.0	0.9	0.5	0.5	0.5	0.3
Kurtosis		0.2	4.3	0.9	3.4	-0.4	0.0	0.7	-0.7
Skewness		-0.4	0.9	-0.4	1.2	-0.1	-0.3	0.5	0.4
Range		5.0	4.9	4.6	5.1	2.6	2.9	3.4	1.9
Minimum		-2.5	-1.9	-2.9	-1.7	-1.6	-1.7	-1.5	0.0
Maximum		2.5	2.9	1.7	3.3	1.0	1.3	2.0	1.9
Sum		4.4	2.9	-10.3	3.2	-2.5	-2.4	5.3	21.7
Count		30	28	21	30	28	30	30	25
Confidence Level of the mean (95.0%)		0.5	0.3	0.4	0.4	0.3	0.3	0.3	0.2

Table 21. Descriptive statistics of the difference between the predicted (default reflectivity) and measured values of solar irradiance for the 60°-sloped surface (no snow season)

Statistics	Month	Apr.	May	June	July	Aug.	Sept.	Oct.	Nov.
Mean		0.2	0.2	-0.2	0.6	0.0	-0.1	0.1	0.8
Standard Error		0.2	0.2	0.2	0.3	0.1	0.1	0.1	0.1
Median		0.1	0.1	-0.2	0.0	0.0	0.0	0.0	0.7
Mode		#N/A	0.0	#N/A	0.0	0.0	#N/A	#N/A	0.0
Standard Deviation		1.2	0.9	1.0	1.5	0.7	0.7	0.7	0.5
Sample Variance		1.5	0.7	1.0	2.3	0.5	0.5	0.5	0.2
Kurtosis		0.2	4.1	1.0	9.1	-0.5	0.0	0.6	-0.8
Skewness		-0.4	0.8	-0.4	2.6	-0.1	-0.3	0.4	0.2
Range		5.1	4.9	4.7	8.1	2.7	3.0	3.4	1.6
Minimum		-2.5	-1.9	-2.8	-1.6	-1.6	-1.7	-1.5	0.0
Maximum		2.6	3.0	1.9	6.5	1.1	1.3	1.9	1.6
Sum		5.3	5.0	-7.4	12.0	-1.0	-2.8	4.1	19.8
Count		30	28	30	21	28	30	30	25
Confidence Level of the mean (95.0%)		0.5	0.3	0.4	0.6	0.3	0.3	0.3	0.2

Table 22. Descriptive statistics of the difference between the predicted (reflectivity predicted by the new model) and measured values of solar irradiance for the south oriented surface (snow season)

Month	Dec.	Jan.	Feb.	March
Statistics				
Mean	1.33	0.58	-0.09	0.46
Standard Error	0.21	0.26	0.22	0.20
Median	0.97	0.29	-0.08	0.49
Mode	0.39	#N/A	-0.18	0.77
Standard Deviation	1.01	1.22	1.17	1.11
Sample Variance	1.02	1.48	1.37	1.24
Kurtosis	0.65	0.89	3.66	0.16
Skewness	1.13	1.17	0.73	-0.21
Range	3.51	4.75	6.36	4.75
Minimum	0.08	-1.04	-2.61	-2.26
Maximum	3.59	3.71	3.75	2.49
Sum	30.5	12.8	-2.48	13.9
Count	23	22	28	30
Confidence Level of the mean (95.0%)	3.59	3.71	3.75	2.49

Table 23. Descriptive statistics of the difference between the predicted (default reflectivity) and measured values of solar irradiance for the south oriented surface (snow season)

Month	Dec.	Jan.	Feb.	March
Statistics				
Mean	0.26	-0.81	-0.96	0.03
Standard Error	0.30	0.17	0.25	0.30
Median	0.06	-0.57	-0.71	0.10
Mode	#N/A	#N/A	#N/A	0.09
Standard Deviation	1.43	0.80	1.30	1.65
Sample Variance	2.05	0.63	1.69	2.73
Kurtosis	0.08	4.98	-0.87	-0.26
Skewness	0.50	-2.02	-0.20	-0.07
Range	5.62	3.48	4.70	6.73
Minimum	-2.06	-3.47	-3.38	-3.29
Maximum	3.56	0.01	1.32	3.44
Sum	6.01	-17.8	-26.8	1.02
Count	23	22	28	30
Confidence Level of the mean (95.0%)	3.56	0.01	1.32	3.44

Table 24. Descriptive statistics of the difference between the predicted (reflectivity predicted by the new model) and measured values of solar irradiance for the 60°-sloped surface (snow season)

Month	Dec.	Jan.	Feb.	March
Statistics				
Mean	1.28	1.04	0.28	0.32
Standard Error	0.19	0.22	0.14	0.14
Median	1.12	1.05	0.15	0.26
Mode	0.50	1.05	#N/A	-0.36
Standard Deviation	0.89	1.03	0.71	0.77
Sample Variance	0.80	1.05	0.51	0.59
Kurtosis	0.35	2.61	0.27	-0.07
Skewness	1.04	1.28	0.49	0.08
Range	3.04	4.46	2.98	3.54
Minimum	0.23	-0.34	-1.09	-1.44
Maximum	3.27	4.12	1.89	2.10
Sum	29.5	22.8	7.30	9.65
Count	23	22	26	30
Confidence Level of the mean (95.0%)	3.27	4.12	1.89	2.10

Table 25. Descriptive statistics of the difference between the predicted (default reflectivity) and measured values of solar irradiance for the 60°-sloped surface (snow season)

Month	Dec.	Jan.	Feb.	March
Statistics				
Mean	0.16	-0.85	-0.34	-0.34
Standard Error	0.28	0.19	0.12	0.21
Median	0.42	-0.81	-0.32	-0.40
Mode	#N/A	-0.81	#N/A	0.03
Standard Deviation	1.36	0.89	0.62	1.16
Sample Variance	1.86	0.80	0.38	1.35
Kurtosis	-0.47	6.75	-0.04	2.60
Skewness	-0.31	-2.12	0.04	1.13
Range	5.15	4.32	2.63	5.65
Minimum	-2.50	-3.98	-1.60	-2.34
Maximum	2.65	0.34	1.03	3.31
Sum	3.75	-18.8	-8.76	-10.3
Count	23	22	26	30
Confidence Level of the mean (95.0%)	2.65	0.34	1.03	3.31