도시계획학 석사 학위논문

Solar Developers' Losses due to Sunshine Duration Shortfall and Marketability of Sunshine Insurance: A Loss Distribution Approach

일조량 부족으로 인한 태양광사업자의 손실추정과 관련 보험 상품의 사업성에 관한 연구: 손실분포법을 이용하여

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국문초록

한국에너지공단 신·재생에너지센터에서 발급한 가장 최신 자료인 2014년 신·재생에너지 통계에 따르면 국내에서 신·재생에너지 믹스에서 차지하는 비중이 4.7%로 폐기물, 바이오 및 수력 에너지 다음으로 가장 높고 태양광 에너지의 증가율은 58.9%로 나타나고 있다.(2014 한국에너지공단). 이처럼 태양광은 국내에서 중요한 신·재생에너지원으로 자리잡았고 RPS 제도의 영향으로 인한 시장 확대 역시 빠르게 진행되고 있다. 따라서 안정적인 태양광 전력 수급이 필수적으로 요구되며 태양광 발전 사업자가 직면하는 위험요소를 줄일 필요가 있다. 태양광 발전 사업자는 여러 가지 시장 위험 (SMP 가격과 REC 가격의 변동성, FIT 지원 여부, PPA 존재 여부), 기술적인 위험 (시스템 성능, 실험 신뢰도, 주변 인프라 수준), 날씨/기후적인 위험 (기상이변, 재난 발생, 일조/일사량 부족)에 부딪힌다. 이 논문에서는 일조량 부족에 대한 집중에 따른 영향의 크기를 해결하기 위해 요구되는 보험상품을 다양한 시나리오를 이용하여 평가하고자 한다.

국내 선행 연구에 따르면 일조량이라는 변수는 태양광 발전량과 0.8 정도의 높은 상관성을 가지기 때문에 일조량 부족은 태양광 발전량에 직접적인 손해 유발의 원인이 된다. 이러한 상황에도 불구하고 일조량 부족 위험을 줄일 수 있는 보험 상품은 국내에서 거의 거래되고 있지 않고 있다. 국내 일조량 부족의 실태와 그 피해를 파악하고 그에 대한 대안을 마련하기 위해서 다음과 같이 몇 단계에 걸쳐 분석을 진행하였다. 일차적으로 기상청에서 제공 가능한 자료 범위 내에서 기준 년도 (1990년 직전 10년 일조시간 평균)에 비해 일조량 변화가 10%(시나리오 1) 또는 20%(시나리오 2) 이상 떨어진 국내 도시의 수가 년도마다 얼마나 발생하는지 추정했다. 이 값을 일사량 부족의 빈도로 사용하였

다. 또한 일사량 부족사태가 일어난 경우에 대하여, 전력거래시장에서 거래하는 태양광 발전 사업자들을 기준으로 1 kW당 수익 손실을 적용하여 일사량 부족으로 인해 줄어든 발전량에 해당하는 화폐 가치를 구하였다. 이 값을 일사량 부족으로 인한 손실의 심도로 사용하였다. 이를 통해 구한 빈도와 심도가 따르는 분포에 가장 적합한 형태를 찾았다. 해당 분포의 형태가 통계적으로 적합한지 확인하기 위해서는 K-S test과 A-D test를 적용했다. 그 후, 적합성 높은 분포의 조합 별로 최대 우도함수(MLE)와 Bayesian Random Walk M-H Sampling 기법을 적용해서 분포의 모수를 구하고서 운영 리스크 관리기법 중 하나인 손실분포법(LDA)를 바탕으로 심도와 빈도 분포를 결합했다. 거기에서 나온 분포에 대한 Simulation을 30번씩 시행하고 위험성 평가로 활용되는 다양한 백분위수 값 (50%, 75%, 90%, 95%, 99%와 99.9%)을 구했다. 백분위수로 얻어진 위험성 정도에 대한 현실 적용 가능성을 보험 회사 입장과 태양광 사업자의 입장에서 논의했다. 그리고 해당 보험 상품의 사업성을 증진시키기 위한 보험의 적절한 구조와 그에 따른 예상되는 보험료를 제시했다. 또한, 기후 변화로 인한 국내 기후 조건이 아열대로 변하고 있는 과정에서 생기는 운량의 증가가 가져오는 일조량 감소에 따라 추가로 발생하는 위험의 크기를 화폐화했다.

이렇게 해서 얻은 시사점 중 첫 번째는 최대가능피해액의 변수로 자주 활용되는 99.9%백분위에 해당하는 피해액은 보험가액 대비 매우 높게 나타났기 때문에 보험 상품의 위험성을 평가할 때 50%에서 75% 백분위에 해당되는 피해액 수치를 활용해야 한다는 것이다. 두 번째 시사점은 예상손실액을 KW당 위험으로 환산하면 기후변화에 따른 추가 예상 손실이 시나리오 별로 약 2.2에서 2.6배가 더 높게 나타났다. 이는 기후변화가 국내 태양광 발전 시장에 대해 기후 변화가 가져올 수 있는 위험의 크기를 보여주고 있

다. 세 번째로 태양광 발전 사업자의 피해액을 더 현실적으로 나타내는 REC를 포함한 시나리오의 예상 손실액이 기준 년도를 1990년으로 고정하느냐 아니면 직전 10년으로 하느냐에 따라 REC 미포함 시나리오에 비해서 1.9에서 2.3배 정도로 커지는 것으로 나타났다. 마지막으로 보험금 지급 조건으로 기준년도 일사량 대비 10% 이상 하락과 20% 이상 하락의 두 가지 기준을 이용하는 경우를 비교해 본 결과 다음의 결론을 내렸다. 각 경우의 피해액에 해당하는 보험료를 고정 비용 또는 에너지 판매량 대비 비용으로 구해본 결과 기준년도 일사량 대비 20% 이상 하락하는 경우 보험료를 지급하는 쪽이 해당 보험 상품의 위험성을 낮출 수 있는 전략인 동시에 NREL(2010) 보고서에서 제시한 태양광 보험의 현실적인 보험료와 유사한 값을 보였다.

- **주요어: 손실분포법, 베이지안 통계학, 최대우도함수법, 몬테카를로 시뮬레이션, 태양광 보험, 기후변화**

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Main Abbreviations		
Abbreviation in English	**Full Name in English**	**Full Name in Korean**
AD test	Anderson-Darling test	앤더슨 달링 검정
C V	Critical Value	임계값
EU	European Union	유럽연합
FIT	Feed-In Tariff	발전차액지원제도
IPCC	Intergovernmental Panel on Climate Change	기후변화에 관한 정부간 협의체
K-S test	Kolmogorov-Sminov test	콜모고로프 스미노프 검정
KEA	Korea Energy Agency	한국에너지공단
KEPCO	Korea Electric Power Corporation	한국전력공사
KMA	Korea Meteorological Administration	기상청
KPX	Korea Power Exchange	전력거래소
LDA	Loss Distribution Approach	손실분포법
MOTIE	Ministry of Trade, Industry and Energy	산업통상자원부
MCMC MH Sampling	Marcov-ChainMonte Carlo Simulation Metropolis Hasting Sampling	마코프체인 몬테카를로 시뮬레이션 메트로폴리스 헤스팅 추출
MLE	Maximum Likelihood Esmination	최대우도함수법
NREL	National Renewable Energy Laboratory	미국 국립신재생에너지연구소
PPA	Power Purchase Agreement	전력수급계약
PV	Photovoltaic	태양광
REC	Renewable Energy Certificate	신재생에너지공급인증서
SMP	System Marginal Price	계통한계가격
VaR	Value at Risk	최대손실가능금액

Appendix

1. LDA Simulation (Bayesian parameters, without RECs, changing base year)

2. LDA Simulation (MLE parameters, without RECs, changing base year)

3. LDA Simulation (Bayesian parameters, with RECs, changing base year)

4. LDA Simulation (MLE parameters, with RECs, changing base year)

5. LDA Simulation (Bayesian parameters, without RECs, fixed year)

6. LDA Simulation (MLE parameters, without RECs, fixed year)

7. LDA Simulation (Bayesian parameters, with RECs, fixed year)

8. LDA Simulation (MLE parameters, with RECs, fixed year)

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1. Introduction

1.1 Research Motivation and Purpose

The 4th IPCC Assessment Report highlights renewable energy's role in climate change mitigation. According to the report, global solar resource available for PV is estimated to be 1,600 EJ/year, making it one of the most attractive mechanisms for climate change mitigation. On the other hand, weather insurance can be regarded as climate change adaptation strategy. (Lecocq F. & Shalizi Z., 2007). Sunshine shortfall insurance can be regarded as both mitigation mechanism and adaptation strategy. On one hand, it reduces climate or weather-induced sunshine shortfall risk to solar developers and on the other, it promotes clean energy generation that acts as a positive feedback in the battle against climate change. Despite of the attractiveness of this synergy, few studies evaluated the current state, challenges and possible improvements to solar insurance.

It is important to note why this paper used insurance instead of weather derivatives to mitigate the risk faced by solar producers. The main reason is that the type of insurance proposed in this paper combines two types of insurance: index insurance and business interruption insurance. This paper sets a strike value for sunshine shortfall based on the historical average. In essence, this is the way that weather derivatives are structured. However, unlike in the case of solar derivatives, sunshine shortfall in itself does not automatically generate cash to solar developers, thereby preventing speculation in solar insurance market. This paper and sunshine-related business interruption insurances offered on the market also require that producers simultaneously experience significant losses because of the sunshine shortfall. This paper considered only losses that result in over 10% solar energy sales revenue decrease. By combining the strengths of index insurance and business interruption insurance, this paper makes sure that insurance money is provided to those producers who are seriously affected by the change in sunshine duration shortfall, thereby reducing the probability of moral hazard problem.

This paper estimates different Value at Risk measures because of their prevalence in assessment of risk in financial institutions. For instance, the international organization, Basel Committee on Banking Supervision, accepts Value at Risk as an appropriate measurement of risk. In the document of Basel Committee on Banking Supervision such as "Consultative Document on Operational Risk" suggest that VaR be measured as 99% level - one of the estimated percentiles of this paper. (Frachot, A., Georges, P., & Roncalli, T. (2001)). Recently, the organization published a framework on the new international standard for financial institutions called Basel III. Starting from 2018, Korean financial institutions will have to comply with Net Stable Funding Ratio under Basel III framework. According to the clause on Net Stable Funding Ratio, a financial entity is required to have available resources in excess of its stable funding. Precise measure of VaR is necessary for the estimation of capital requirement that financial institution should have in liquid assets in order to cover operational losses. VaR essentially instructs the financial institution how much of the money an insurance company should have on hold or in liquid assets to meet its coverage obligations in the worst case scenario. Therefore, if VaR is too high, a company will be more likely to hesitate entering the industry or is only willing to do so while receiving high premiums. Therefore, only large insurance companies with many assets will likely sell risky insurance. On the other side, consumers, PV developers in this case, have to balance the relative gains, costs and importance of the sunshine duration insurance in comparison to other forms of risk. The next part of this chapter introduces diverse risks faced by solar developers worldwide.

1.2 Risks of Solar Developers

Solar developers are exposed to various forms of risk. Some of the most important risks are solar generation uncertainty, Renewable Energy Certificate (REC) price risk, FIT policy existence and coverage, System Marginal Price (SMP) risk, photovoltaic (PV) installation and maintenance cost. National Renewable Energy Laboratory produced a report in 2010 outlining the importance of solar insurance and its relative burden to the solar developers. The report states that PV insurance can affect the energy price produced from this source and competition within the industry.

Furthermore, National Renewable Energy Laboratory′s (2013) ‘Continuing Developments in PV Risk Management: Strategies, Solutions, and Implications’ report (further referred to as NREL(2013)) stated that cost of capital for PV projects can be reduced in case of effective risk management. Resource estimation risk, which stands for the confidence that the historical solar data is a reliable source of future solar yield, is the premier source of technical risk first mentioned in the report. Traditionally, both PV energy developers and insurance companies use 10 to 15 years of historical data from the closely located meteorological station or summary documents to estimate the sunshine resources in the specific area. Unfortunately, these are not always good predictors of the future revenue and shortfall occurs. Despite being one of the most direct risks discussed in this paper, no article questioned the significance of solar shortfall relative to other forms of risk in solar energy development. However, poor management of this risk type can lead to resource-related production shortfalls, debt service delinquency or default (NREL, 2013). Kim Y. and Shim G. (2013) pointed out that it is impossible to predict future PV efficiency and thereby future cash flow due to variability in sunshine duration. Korea Insurance Research Institute (2012) also acknowledged the presence growing of weather risk as the number of renewable energy installations rises in Korea. Improvement of revenue predictability is not the only benefit of insurance. Stable revenues also allow the energy developer to get a loan from banks at a lower interest rate. (Peterson N. (2012))

Resource estimation risk is not the only technical risk that deserves attention. Other important risks include component specifications risk, i.e. performance specifications of the selected product; system design, which is integration of components, their availability and reliability; performance estimates and acceptance/commissioning testing, i.e. the tests signaling the validation of PV's performance; site characterization, which include environmental and infrastructure specifications, and transmission cost; and finally transport/installation risks, which explain the equipment damage delays. (NREL, 2013)

In addition, solar developers bear significant non-technical risks. Non-technical risks include transmission/distribution and interconnection risks, which can result in cost overruns and project delays; developer risk, i.e. personal experience and proficiency of the developer; availability of power purchase agreements, which guarantee that an entity will buy a certain portion of the energy produced by solar developers. The latter risk contributes to financial stability of solar developers, and plays a crucial part in solar developersʹ ability to stay in the business. Also, a PV developer faces construction risks, which include weather and natural disaster-related disruptions; control over development site, risk diversification level to multiple stake-holders; weather and resource risk, related to business interruption from naturally occurring events; and price volatility of commodities required to install PVs. Some companies such as Aon or Hyundai Marine and Fire Insurance consider sunshine shortfall a type of business interruption insurance.

Policy/regulatory risks, such as Feed-In-Tariff (FIT) and/or Renewable Portfolio Standard (RPS) policies, permits etc. are also viewed as more important than any other source of risk in Korea (Korea Energy Agency, interview). This is understandable because solar energy is heavily reliant on Renewable Energy Certificates (RECs) or a form of subsidy (FIT). In fact the price per KW for RECs is approximately as high as the SMP (Systems Marginal Price, which is equivalent to the highest hourly price among different types of energy for mass production), while FIT was as high as 6 times the SMP in 2015 making a significant portion of solar developersʹ revenue. In 2015, REC price volatility was about 6%, which is not little considering it is just one type of risk. Predicting and integrating the risk of SMP and REC price is another huge topic which is dependent on government policies, energy supply and demand and others. That is why current sunshine shortfall insurance available in Korean market does not include them in calculation and estimates consumer losses solely on sunshine duration or radiation variable. However, this paper tried to provide a general picture of how the amount of losses would change if PV developersʹ losses included both solar SMP price and REC price in the calculation of their losses. That will be presented as a separate scenario in this paper. Before presenting the scenario, the paper will provide a summary explanation about Korean solar market structure and variable influencing solar development.

2. Solar and Insurance Market

2.1 Korean Solar Energy Market

2.1.1 Market and Policy Structure Overview

South Korea adopted Feed-in-tariff (FIT) policy in 2002 but discontinued it by the end of 2011 on the grounds of excessive government budget spending. It switched to Renewable Portfolio Standard (RPS) in 2012. That led the Korean government to adopt RPS policy instead in 2012. However, FIT policy promised to apply FIT to solar installations for 15 to 20 years.[1] Therefore, some solar developers′ contract that was concluded under FIT policy is still valid, so government supports those producers with the subsidy. Likewise, currently solar developers that trade in Korean market can be divided into two groups based on the type of compensation that they receive. The first group constitutes 62% of the total solar developers and receives sales revenue under Renewable Portfolio Standard. This group gets energy price (a little higher than SMP price because solar energy is abundant during hot summer peak time periods) and REC in exchange for selling solar energy. The rest 38% as of the end of 2015 receive the base price. The base price consists of subsidy equivalent to the summation of SMP and the remainder of subsidy in form of FIT. For the purpose of simplicity, this paper renamed base price as total ″subsidy for FIT installations″. FIT protects solar developers from SMP volatility risk.

There exist a number of variables that influence compensation that solar developers receive. However, solar installations are classified as non-emergency equipment and therefore the earnings from energy sales are restricted to SMP.[2] SMP changes depending on how much the demand is at a certain hour and/or weather conditions (also related to the demand issue). Furthermore, solar energy sector is not yet operating by demand and supply rules. In fact, a government sets yearly targets that renewable energy obligation companies have to achieve and plans REC spending from based on the target solar installations. Other smaller developers have only marginal influence on the solar energy

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[1] MOTIE (2010.09.27) "Guideline on Base Price for New and Renewable Energy Use and Power Generation". Article 10 (2). Retrieved from http://www.law.go.kr/%ED%96%89%EC%A0%95%EA%B7%9C%EC%B9%99/ on June 1st, 2016.

[2] KEA (2016) ″Electricity Market Operating Rules″. Retrieved from http://www.kpx.or.kr/www/selectBbsNttView.do?key=29&bbsNo=114&nttNo=14777&searchCtgry=&searchCnd=all&searchKrwd=&pageIndex=1&integrDeptCode= on May3d, 2016.

prices. Therefore, it is safe to conclude that PV developers′ profits depend on SMP and REC price.

Another important aspect of Korean solar energy market is the existence of quota for solar developers in the total mandatory renewable energy mandatory yearly supply. The mandatory energy supply for alternative energy sources (including solar specific quota) was 12,339,927 MWh. Mandatory solar energy supply was 1,971,000 MWh, which constitutes 16%. In a personal interview with Korea Energy Agency Renewable Energy Center representative, it was clear that the lack of additional space for large solar installations does not give motivation to government officials to increase the percentage that solar energy shares in the total renewable energy production. To summarize, government policy is the decisive force on REC price, and current trends suggest that the law of supply and demand has little to do with the total availability of RECs in the market.

2.1.2 State of Solar Insurance in Korea

The efficiency of weather insurance in general was assessed in the CME and Storm Exchange Inc. survey of 2008 which indicated that 59% of energy companies felt the need for protection from adverse weather events. (Kim Y. (2012)). Park G. et al. (2013) performed a survey of energy, weather, leisure and manufacturing specialists of 274 people on necessity of weather insurance in Korea. Of those, 60.3% reported they experienced losses due to weather variability.

Even though the importance of solar duration to solar developers' revenue is heavily dependent on sunshine duration, Korean insurance companies have difficulty selling the insurance to solar developers. According to a Korean insurance newspaper (Bohom Maeil), insurance companies are even considering withdrawing from weather insurance business. According to the newspaper's article of September 20th, Samsung has been selling business interruption weather insurance from June 2012. However, the company only had one customer whose contract was expired without renewal. Similarly, Hyundai Marine and Fire Insurance had only 3 contracts related to business interruption from weather events. Other insurance companies that offer this product domestically are Samsung Marine and Fire Insurance, Dongbu Marine and Fire Insurance and Aon Insurance. In an interview with these insurance companies, it was clear that currently they are skeptical about this type of insurance. The reasons that the interviewees gave were high risk due to lack of data and experience, and difficulty in predicting the shortfall in sunshine duration or radiation.

The reviewed insurance contracts did not include any variables other than sunshine duration (or solar radiation as a proxy) in loss severity calculation because that could make calculations confusing and instigate moral hazard problems. If the insurance contract proclaimed to cover the total solar generation losses, the insurer would have to consider variability in REC, SMP etc. However, sunshine duration insurance considers only one source of risk - sunshine duration. Therefore, revenue from solar generation relied only on three variables: solar installations, electricity price and daily average sunshine duration. Nevertheless, for the purpose of more realistic assessment, this paper includes a case when insurance policy incorporates REC price. Unfortunately, estimating REC trend from historical data is very challenging since the period of historical data is short and oftentimes available data is not continuous. Therefore, this paper used 2015 year average REC price for the estimation of VaR with RECs.

2.2 Foreign Solar Energy Markets

2.2.1 Market and Policy Structure Overview

Solar markets are different across the globe and are some of the most rapidly growing markets at the moment. In cases of Europe or Japan, solar markets are more mature than those in the United States. However, the newcomers, such as China are substantially changing the rankings of global top PV installers. PV Status Report 2014 states that at the end of 2013, EU had cumulative generation capacity of 80.7 GW. Germany's cumulative PV capacity was 40 GW at the end of 2015. China, a late comer in the industry, emerged as a significant PV generator in 2010 and is a current world leader in cumulative capacity with cumulative 43.2 GW as of December 2015. Japan also had considerable PV installations of 39.7 GW by the end of 2015. On the other hand, United States' capacity was 25.6 GW by the end of 2015. India lacks far beyond the other key installers but is rapidly expanding PV installations. In 2015, India exceeded 4 GW of solar installations. In comparison, Korea only had 3.2 GW of cumulative solar installations by the end of 2015. (Korea Energy Agency, internal source)

Aon Risk Solutions considers Asia Pacific region to be an important region in PV property damage/business interruption insurance industry. The company estimates that this sector of insurance industry will exceed USD 1 billion in 2020. Insurance is still viewed as the primary risk mitigation option, used by 60% of executives for risk transfer in Europe, Australia and North America. The second most favorite option was weather-related derivatives.

2.2.2 State of Solar Insurance in Largest PV Economies

This paper reviewed PV generation-related insurance policies of different countries, most of which bear resemblance to the insurance type described in this paper. These included HSB solar shortfall insurance for lower than normal solar radiation (Munich Re) and LDK Solar insurance that covers all on-grid solar modules but for projects over 1 MWp. Yet, the reality is that sunshine duration affects all solar developers in the region, leaving out smaller developers unprotected from business interruption due to unprecedented solar duration shortfall. That is why it is imperative to develop protective measures that could be applied to all solar developers, even those with capacity under 1MW. This paper considers the risk of covering all solar developers that trade solar energy in the Korean market. Japan Yoneyama Seminar (2014) reported that some Japanese non-life insurance firms provide compensation contracts for covering losses caused by poor sunshine duration. Allianz Insurance also pays solar radiation insurance indemnity if the yield from solar panel is lower than the predetermined variation.

2.3 Challenges in Solar Insurance Market

2.3.1 Issues Overview

The unfortunate state of solar insurance in Korea, in particular, and in the rest of the world, in general, is not a coincidence. Developing solar insurance into a product is risky due to the novelty of the technology and the related lack of loss data. (NREL, 2010) The domestic companies, which have not yet implemented solar insurance, have to either benchmark the insurance of their foreign counterparts or make rough predictions about the risk. Either of the approaches is prone to be filled with risk management errors. For instance, in Korea government institutions such as KEPCO and KPX store information about solar developers from year 2007. Solar installations existed prior to that period, but occurred sporadically. According to KEPCO (2008) the total solar photovoltaic development installations were approximately 29 MW in 2007. That amount increased to 3,163 MW of photovoltaic installations by the end of 2015. (KEPCO, internal data) This partially explains the novelty of South Korea's solar insurance products. Comparatively, solar insurance was debated in the U.S. by NREL as early as in 1999's report "Solar Technology and the Insurance Industry: Issues and Applications".

Based on the experience difference, some countries became more and more proficient in solar insurance business, whereas others remain behind, which further broadens the gap. Since the European PV insurance companies have longer history than their U.S. or Korean counterparties, European companies have better understanding of the associated risks. Therefore, many U.S. insurance companies often rely on the EU data to analyze the risk of an insurance product, as mentioned in “Insuring Solar Photovoltaics: Challenges and Possible Solutions”. (NREL, 2010) Similarly, Korean companies often choose to predict the risk by adjusting the U.S. data. However, the climatic and regulatory difference remains, driving insurance premiums up. That is why it is important to analyze the current risk that solar insurers face based on the domestic data.

Another issue with the solar insurance industry is that there are few insurance companies offering coverage for solar products, effectively leading to oligopoly. In fact, Samsung, Hyundai and Dongbu Fire & Marine Insurances are the only active domestic companies that offer sunshine shortfall insurance in Korea. Many of them struggle to retain their customers and attract new ones. Similarly, until 2010 Lloyds of London was virtually the only insurance company that underwrote insurance solar developers in the United States. (NREL, 2010) Lack of competition creates a sluggish environment and discourages companies from coming up with creative solutions to the solar insurance problem.

Furthermore, the costs of insurance premiums are high, making them unattractive to customers. Insurance premiums constitute almost 25% of a PV system's annual operating expense. The total insurance premiums range from 0.25% to 0.5% of the total fixed cost of a solar development project. When compared to the cost of energy, insurance for PV developers comprised 5% to 10% of the total cost of energy from installations. That is considered to be high since PV installations require virtually no maintenance costs to operate. (NREL, 2010)

Yet another problem comes with economies of scale. Since less people have installed PV than, for instance, bought a car, insurers cannot use "law of large number" to predict insurance losses accurately. In other words, it is uneasy to spread the risk with the high number of solar insurance subscribers.

Naturally, the insurance risk will be different from company to company depending on the volume of energy production, renewability cycle of the contract and success of claim proof. Considering the current contractual arrangements in Korean solar generation insurance companies, and the simplicity of the insurance structure, this paper assumes that the insured party does not require the proof of the actual revenue loss due to solar duration shortfall and the losses are compensated according to the formula specified in the model. Furthermore, the contract is assumed to last under the same terms for as long as the installations are running.

Despite of the fact that solar developers face diverse source of risk, they occur at different stages of a project for solar energy development. Sunshine duration risk occurs during the operation phase of solar project. While other natural phenomena, such as hurricanes, thunders, floods are often included in total insurance along with sunshine duration shortfall, this study reviews sunshine duration separately. It is because sunshine duration shortfall was the most understudied topic, deserving special attention and also because the sunshine duration shortfall follows a quite different loss distribution. Bum Seo Kang (2013) and other studies of natural disasters confirmed that the loss distribution of these natural phenomena follows heavy-tailed distribution. Sunshine duration, as will be revealed further has less heavy tail but also follows lognormal distribution.

2.3.2 Impact of Climate Change

The uncertainty grows with climate change. Munich Re (2005) reported that natural disasters coincide with global warming. This risk is translated into high insurance premiums for solar developers. This field is also viewed risky because it is heavily driven by state policies and incentives that could be terminated at any point and result in shrinking solar developers' market. The only way that insurance companies can survive in weather insurance industry where there is a clear increase in losses due to climate change is by increasing premiums for the service. The flip side of the issue indicates that businesses and private parties will be forced to buy more and more of this type of insurance if their profits are significantly affected by the climate change.

One of the most growing insurance businesses is catastrophe insurance. In fact the penetration of this insurance is quite high already: it accounts for 9% of the GDP in the developed world and 5% in the developing countries. However, most of the insurance is focusing on agricultural or public sector rather than renewable energy. Climate change acts upon insurance sector in the following ways: (i) the time between loss events gets shorter; (ii) variability of losses increases; (iii) events become different in structure; (iv) the location of events changes; (v) a small increase in weather intensity leads to severe catastrophes (e.g., wind damages rise with the cube of the speed); (vi) relationship in losses is nonlinear; (vii) losses are not confined to one area (e.g., from tidal surges arising from a broad die-off of protective coral reefs or disease out breaks on multiple continents); (viii) the number of stand-alone events with disruptive consequences increases. (Mills E. (2005)).

Interestingly, climate change seems to be revealing itself even in case of sunshine duration shortfall insurance. Currently insurance companies in Korea consider a case when sunshine insurance falls behind a certain threshold of *directly* preceding average sunshine hours. When analyzing this sort of data, the sunshine shortfall revealed no trend. This is because defining shortfall as less than 90% solar duration of the preceding 10 year historical average affectively eliminates any trend in insurance claims probability. However, if insurance's terms were arranged differently, the insurance company would have to account for long-term trends in the climatic conditions. After observing that severity of the losses got larger when the shortfall is compared with fixed 1990 year as a historical reference point, I looked for scientific explanation to this phenomenon. My assumptions turned to be supported by the long-term trend tracked by Korean Meteorological Agency. In Korea's case, sunshine duration is gradually decreasing due to prolonged rainy periods. In fact, in 2014 National Climate Service Data System of Korean Meteorological Agency uploaded information that from year 2004 to year 2014 sunshine duration decreased by 0.5%/year on average. Rural Development Administration confirmed the trend with the study of 60 locations in Korea over the period between 1973 and 2010. Therefore if the historical reference point of sunshine shortfall stays unchanged for a long period, insurance companies will have to increase insurance premium due to climate change. To interpret the climate change risk into monetary information, this paper will replicated the analysis of the standard scenario with the only change in reference point (which will be fixed at sunshine duration value of the year 1990). However, this result should be interpreted with caution. While decreasing sunshine duration is a scientific fact, it is also true that solar radiation is increasing on the Korean peninsula. Sometimes these two are interfering with each other. Yet, this paper claims that sunshine duration is a more appropriate measurement for PV developers (since it measures the amount of light), whereas solar radiation is a more appropriate measure for solar heating plants (since radiation measures the strength of the ray and heat transfer).

3. Research Scope and Methodology

3.1 Research Scope

This study focuses on the first source of risk, solar generation uncertainty with the emphasis on the most important factor in PV energy generation - sunshine duration. Korea Meteorological Administration (KMA) defines sunshine duration as the total amount that solar rays reach the surface without being obstructed by clouds or other objects. This variable is theoretically more closely related to PV generation than to solar power generation. Seo M. (2016) estimated in an empirical study that sunshine duration was the most direct predictor of actual solar generation in PV in Korea. The higher predictive value of sunshine duration over solar radiation was supported by Cheongju's inverters

2012~2014 actual solar generation data. The Pearson's correlation coefficient between solar energy generation and sunshine duration was 0.815. The high coefficient of correlation justifies the promotion of sunshine duration insurance in Korea.

This paper strived to account for all publicly accessible information regarding PV installations and sunshine duration data. This paper analyzes South Korean 54 cities' and counties' yearly sunshine duration shortfall and the corresponding revenue losses from 1990 until 2015. Although the actual estimation of losses due to sunshine duration shortfall starts from year 1990, this paper considers the preceding 10 year (from 1980 to 1989) average of sunshine duration to estimate 1990's sunshine shortfall.

The study is limited to 54 cities and counties because out of 57 meteorological stations located in cities or collecting sunshine duration data in South Korea, 3 (Ganghwa_gun, Seongsan, Ulleung) did not have market participating solar developers. The map in figure 1 indicates the location of meteorological stations whose data was analyzed in this paper on the map of South Korea. The darker blue color stand for the stations that were analyzed while the brighter blue color indicate the ones that were left out due to the lack or inconsistency of data.

Since solar duration is considered an aggregate risk, rather equally affecting all of the solar developers in the same region, this paper sees no reason to leave out any of the PV energy developers. Therefore, to analyze all affected parties, this paper considers all solar developers trading solar energy in the market. Information on solar generation for personal consumption was left out of scope of this paper since government institutions do not disclose such information on privacy grounds.

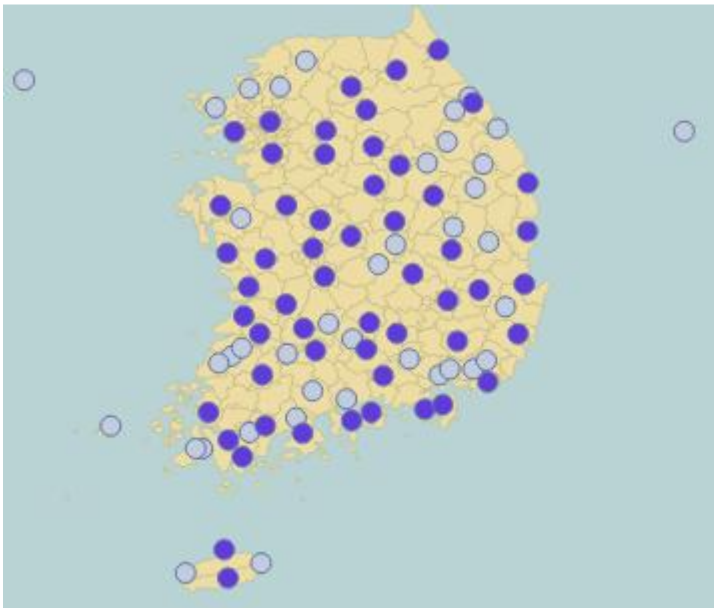

Figure 1. <Location of Meteorological Stations for the Study>

Source: KMA

3.2 Study Methodology

To get the sense of risk probability across different cities, this paper will fist adopt the Bayesian inference approach for each evaluated city. Based on Markov-Chain Monte Carlo simulation (MCMC simulation), the paper will estimate the probability of sunshine duration shortfall at 99% and 99.9% level. In addition, in attempt to see if solar insurance can be more realistic under less extreme cases, this paper also provides summaries of 50%, 75% and 90% cases. The reason for incorporating these unusual risk estimates is as follows. In an interview with Samsung Life & Marine Insurance researcher, I found out that insurance industry has reached a consensus that renewable energy projects are riskier than the traditional projects. Therefore, to make these projects more realizable companies often lower the standard. For instance, 75% risk for wind insurance was used as a risk reference measure instead of 99% or 99.9% measure. Another reason is that sometimes the estimated value of the losses exceeds the reasonable bounds, such as total insured value or in this case the proxy for it (estimated yearly revenue). Furthermore, professor So Jung Park of Seoul National University, who is specializing in business and insurance provided a valuable feedback on the way to estimate the approximate insurance premium knowing 50% percentile (expected) shortfall, making it possible to interpret the results from the consumers′ perspective.

This paper will first and foremost assess if the downside risk of sunshine duration is significant enough in Korea by analyzing the number of instances that sunshine duration fell below the historical 10 year average in each city where sunshine duration data is available. Second, it will evaluate the risk of sunshine duration shortfall in each city using Bayesian approach. Then, it will analyze the maximum aggregate possible loss for current solar developers using Loss Distribution Approach (LDA) and Maximum Likelihood Estimation (MLE) Methodology.

In order to estimate the loss using Loss Distribution Approach, this study will estimate the frequency and severity of losses based on the reference material of actual insurance products regarding the shortfall of sunshine duration. This paper will further evaluate the frequency and severity distributions based on the review of theoretical literature and the fitness of the distribution using Easyfit 5.5 Professional(Mathwave) software. To test the fit of the suggested distributions, this paper will analyze the fit in R using Kolmogorov-Smirnov test and Anderson-Darling test, which provide statistics of fitness of how well the actual data fits the estimated distribution.

This paper will compare the outcomes of traditional numerical estimation of parameters using MLE estimation with the Bayesian inference using MCMC simulation. The former approach is adopted to overcome the shortcoming of rather small data set. This type of inference is often used in the estimation of meteorological disasters and rare events in nature. Upon selecting the relevant conjugate prior for the fit distribution and conducting MCMC simulation using Metropolis-Hasting sampling with random walk in Rjags, the paper will evaluate the parameters. Finally, the paper will combine the frequency and severity through conjugation approach to arrive at the congregate risk measures.

For the completeness of the analysis and comparison between the likely states of the reality this paper will not just consider the current type of insurance, but will also evaluate how risk and estimated premium changes when sunshine duration insurance incorporates RECs and the case when sunshine duration insurance is impacted by climate change (through fixing the base year). The combinations of these realistic scenarios yield 8 separate cases since all of them are estimated both by MLE and through Monte Carlo simulation. Risk at different levels assessed through LDA approach for each of the 8 cases is then repeatedly simulated 30 times each for precision. All of the simulations are organized in the tables of Appendix A.

This paper will use R and Matlab R2012a (Mathwork) program for MLE estimation; and Rjags for MCMC simulation.

4. Theoretical Background and Literature Review

4.1 Theoretical Background

4.1.1 Loss Distribution Approach

The methodology applied here is Loss Distribution Approach. This approach measures operational risk at both Basel business line and event type levels. LDA includes three components: frequency, severity and an aggregation of the two distributions. This study answers the question whether loss frequency and loss severity from sunshine duration follows the distribution similar to the extreme events' loss severity. Loss Distribution Approach sums the risks on yearly basis from each case/ company/city (in this case). Then it estimates which parameters best describe the yearly distribution of frequency and severity distribution separately. Through conjugation of severity and frequency, this approach aims to arrive at the possible maximum risk.

Loss Distribution Approach is often used as an alternative to Score Card. Score Card approach is often used in strategy. A score card accounts for different characteristics of data with pre-assigned weights. This approach requires subjective opinion on the value of each characteristic, but it is suitable when comparing alternatives that are best for accomplishing a particular goal.

4.1.2 Probability Distributions

Frequency distributions usually follow one of the following discrete distributions: Binomial distribution, Negative Binomial distribution, Poisson distribution, Uniform distribution, Geometric

Distribution. Uniform distribution denotes a distribution in which all outcomes are equally probable. Binomial distribution is used to predict the number of successful trials. Negative Binomial distribution gives information on the trial number when r^{th} success occurs. Poisson distribution tells the number of events that occur in a certain period of time or at a certain location. Finally, Geometric Distribution describes the number of Bernoulli trials to achieve one a success. It could also be interpreted as the probability distribution of the number of failures before the first success.

Loss severity usually follows the heavy-tailed distributions, such as Pareto distribution, Gamma distribution, Weibull distribution and Log-normal Distribution, among others. Hossack I. et al. (1999) indicated that Pareto distribution if useful for large disastrous events; log-normal distribution is appropriate for positively skewed distribution in cases where the insurance should pay a large number of small indemnities; gamma distribution is applied for the analysis of total yearly losses yearly losses. However, the severity data in this study was fit for normal distribution, which is uncharacteristic of the insurance losses in general.

4.1.3 Probability Fitness Tests

To correctly estimate the distribution that fits the data this paper performs Kolmogov-Smirnov and Anderson-Darling Tests. Kolmogorov-Smirnov test is a non-parametric test based on empirical cumulative distribution. This test is only applicable to continuous distributions. This test is more sensitive to the center of distribution.

$$D = \sup_x |H_n(x) - H(x)|$$

(Equation 1)

Another important statistic that can tell us whether the data fits well to the distribution is Anderson-Darling Test. This test gives much weight to tail observations. Generally, A-S test is considered more powerful than K-S test since it is more sensitive to the null distribution. A-S test is written in the following manner.

(Equation 2)

$$A^2 = n \int_{-\infty}^{\infty} \frac{(H_n(x) - H(x))^2}{H(x)(1 - H(x))} dH(x)$$

4.1.4 Estimation Methods

(1) Maximum Likelihood Estimation

Traditional statistical methods use Method of Moments, Maximum Likelihood Estimation and Lest-Squares Method for parameter estimation. Among those, MLE sets the least restrictions on the estimation of parameters.

$$l(\theta | Y_1, Y_2, \cdots, Y_t) = f_t(Y_1, Y_2, \cdots, Y_T | \theta) = \prod_{t=1}^{T} f(Y_t | \theta)$$

(Equation 3)

The definition of the likelihood function for MLE is written in the equation above.

In the equation, $(Y_1, Y_2, \cdots, Y_T)$ denote random variables; $f_t(y1, y2, \cdots, yT | \theta)$, $\theta \in \Omega$ is the parameter space. The assumption for MLE is that the sampled observations are independent and identically distributed (iid). The lack of sunshine in under the proposed design was not shown to follow some specific trend when Mann-Kendal test for trend in time series data was performed using XLSTAT 2016 software.

(2) Bayesian Estimation

Bayesian inference gained its popularity in the 21s century. The main difference between classical statistical inference, such as MLE estimation and Bayesian inference is that the latter views parameters as random variables. Therefore, probability theory is in the roots of Bayesian inference. To estimate the parameter, Bayesian inference takes into account all possible prior information through conjugate prior distribution and combines it with the likelihood of the event to generate posterior distribution. The limitation of this approach is that prior distribution should be selected based on the subjective opinion of the researcher.

The Bayes' theorem provides and expression of conditional probability of event y in the following manner (equation 4). Here, f(y|θ) and π(θ|y) refer to a posterior distribution, whereas π(θ|y) and f(y|θ) refer to a prior distribution. Finally, f(y) and π(θ) refer to the likelihood functions.

(Equation 4)

$$f(y|\theta) = \frac{\pi(\theta|y)f(y)}{\pi(\theta)} = \frac{\pi(\theta|y)f(y)}{\int_{-\infty}^{+\infty} \pi(\theta|y)f(y)dy}$$
$$\pi(\theta|y) = \frac{f(y|\theta)\pi(\theta)}{f(y)} = \frac{f(y|\theta)\pi(\theta)}{\int_{-\infty}^{+\infty} f(y|\theta)\pi(\theta)d\theta}$$

The simplified form of the Bayesian expression is expressed in equation 5. The expression is in form of a proportion since it does not have expectations on each side. Setting expectation value on the right hand side is challenging since it requires integration. Therefore, instead the analysis is made numerically through the MCMC simulation.

(Equation 5)

$$f(y|\theta) \propto \pi(\theta|y)f(y)$$
$$\pi(\theta|y) \propto f(y|\theta)\pi(\theta)$$

This paper did not restrict analysis to restrict its attention to classical statistical inference in order to exploit many advantages that are offered by Bayesian statistics.

OíHagan, A. and West, M. (2010) offer four main advantages of Bayesian inference. First, Bayesian inference is consistent with axioms of rational inference, making it fundamentally sound as opposed to non-Bayesian inference that occasionally relies on fuzzy logic. Bayesian inference provides a rigid framework for analysis - selection of likelihood and prior distribution to arrive at posterior distribution. However, Bayesian approach also offers freedom to choose which information to include and which to exclude, which is not possible in classical statistical inference. Bayesian inference provides more direct interpretation of the intervals. For instance, Bayesian "credible interval" implies that the actual value of interest lies inside of the 95% boundaries and takes random value. On the other hand, frequentists' "confidence interval" takes the boundaries as random values informs the reader that the fixed value lies in the interval 95 experiments out of 100. The latter logic is more challenging to understand and apply, especially when the number of experiments is low. Finally, in many cases, subjective information becomes a valuable addition to the conventional statistical knowledge about a situation. That could be extra information on the behavioral patterns or situational boundaries. When professional opinion about the prior distribution matches the reality, it is possible to make more precise predictions about the examined variable.

Various sampling designs have been introduced for MCMC simulation in Bayesian inference. Bayesian inference requires MCMC simulation because it is impossible to repeat some natural events under the same conditions. Of the two most popular sampling algorithms, Metropolis-Hastings sampling and Gibbs sampling. This paper will use JAGS with Metropolis-Hastings (M-H) sampling algorithm. This selection was made based on the property of M-H algorithm to result in convergence regardless of the proposed distribution. It will use random walk for sampling procedure since it allows for the most general sampling when information about the parameters is lacking. Metropolis-Hastings algorithm is a special case of M-H algorithm with $q(x, y) = q(|y - x|)$. Random variable y is expresses as $y = x + z, z\ q(|z|)$, where z is white noise. M-H sampling follows the following steps:

i) Select the appropriate x0 as the initial value

ii) Select y from the suggested distribution $q(\cdot\ |x_t)$

iii) Generate random numbers (u_t) from Uniform distribution (0,1)

v) Update Update $x_t + 1 = y$ with probability of α and $x_t + 1 = x_t - 1$ with probability $1 - \alpha$

Although it is desirable to consider error in parameter updating as time-varying, this paper will assume that error variance is constant for the simplicity of the analysis.

4.2 Literature Review

This paper will analyze literature in two steps: first it will review the Korean and foreign development in research on sunshine duration and other weather insurance. Second, it will review the loss estimation methodology that will be employed in this paper.

First, Park S. (2012) suggested sunshine deficit index (SSD), where cumulative sunshine deficit index (CSSD) is expressed in equation 8.

(Equation 8)

$$CSSD = \sum_{i=1}^{N} max(\overline{sunshine_i} - sunshine_i, 0)$$

The sunshine duration insurance employed in this paper is a combination of index insurance and business interruption insurance. Insurance indemnity is dependent on both the index (which changes slightly every year along with the changes in preceding 10 year average) and the severity of the event (the sunshine duration shortfall should be over 10% of the preceding 10 year average). Since there has been no research on the sunshine duration insurance to solar developers that the author is aware of, this paper will consider similar insurance designs in other fields.

The hypothetical payouts to rainfall insurance were estimated by Gine X. et al. (2007). This paper did not have the actual claims data but estimated the losses based on the rainfall index insurance policy and the number of contracts since 2003.

Wilson P. & Toumi R. (2005) assessed the probability distribution of rain in United Kingdom and found that Generalized Extreme Value (GEV) distribution fits well for daily maximum precipitation. They estimated the parameters using MLE approach.

Roberts R. (2005) illustrates various examples of index insurance for crops in developing countries. In Philippines, the agricultural insurance is operated by parastatal entity and offers protection against cyclones.

Kang B. (2012) used LDA method to estimate maximum damage to public property from natural disasters using publicly available yearly data of loss frequency and severity. This study also used MLE estimation and Bayesian inference to arrive at 95% and 99% loss.

Park J. (2007) estimated loss distribution using MLE function, whereas Bakhodir E. (2009) used the mixture of gamma and log-normal distribution with M-H sampling to estimate loss distribution with heavy tails.

Lee Y. et al. (2008) estimated VAR by adopting both MLE and MCMC simulation. He investigated the case of air flight cancellations due to adverse weather conditions.

5. Data & Assumptions

5.1 Assumptions

Unlike in the case of natural disasters, the impact of sunshine duration itself is not a variable that incurs losses. Therefore, it requires theoretically sound criteria for defining "sunshine shortfall". The majority of studies that deal with sunshine duration-based weather insurance are applied to agriculture, not energy sector. One of the non-agricultural applications of "sunshine shortfall" insurance was introduced in Japan. It covers beverage companies who experience revenue decline due to sunshine shortfall. However, since the industry is different this product cannot be used as a criterion for sunshine shortfall to solar developers.

Due to the lack of assessment criteria in academic literature, this paper had to incorporate current calculation practices of Korean and foreign insurance companies that offer compensation for foregone revenue due to the loss of sunshine duration. This paper mainly adopted the loss estimation methodology from solar generation insurance contracts of companies that operate in Korea. (received from internal source) Most companies use preceding 10~15 year sunshine duration average for the calculation of solar shortfall frequency. In other words, companies would provide compensation in case sunshine duration falls beyond preceding 10~15 year threshold. However, since this criterion leaves insurance companies exposed to high risk, they specify additional requirement for the trigger of insurance indemnity - that the corresponding loss of profits should a certain amount (usually 10%) of predetermined minimum profit. Another requirement that could be used instead specified that solar duration should fall over 10% below the preceding 10 year average. (Samsung Fire & Marine Insurance, Solar World). After considering the aggregate risk under this scenario, the paper also reviewed the situation where sunshine shortfall is defined as average sunshine duration hours that are 20% below the historical average. Since this paper does not have access to the predetermined minimum profit, it will use the former method of calculation a sunshine duration shortfall event in a specific city. Finally, insurance companies often set coverage boundaries to protect themselves from extreme downside risk. However, the practice varies from company to company and would require arbitrary adjustment on my part. Therefore, the limit of the coverage is left to the discretion of insurance company and is not considered in this paper.

Considering the estimations in the reviewed documents, this paper calculates the frequency of sunshine duration shortfall and the severity of revenue foregone due to this shortfall in the equations 6 and 7.

(Equation 6)

$$\text{Let city } i\text{'s Sunshine Shortage} = (\overline{\text{city}_i'\text{s sunshine duration}} - \text{city}_i'\text{s sunshine duration})$$

$$\text{If Sunshine Shortage} > 0 \text{ and } (\text{Sunshine Shortage} / \overline{\text{city}_i'\text{s sunshine duration}}) > 0.1\ (or\ 0.2\ for\ scenario\ 2) \rightarrow i = 1,$$

$$\text{otherwise} \rightarrow i = 0$$

$$\text{For } i = 1, \ldots, N$$

$$\text{Sunshine Shortage for } k^{th} \text{ year(shortage event frequency)} = \sum_{i=1}^{N} i$$

Although electricity price and solar installations also have change during the assessed period, this paper will assume that they were fixed at the present level (average 2015 for electricity price and total solar PV installations by December 31, 2015). If assumed otherwise, the frequency and severity of the losses will be affected, rendering distribution analysis biased. The information on total market participating solar installation by city as of December 31, 2015 was obtained from Korea Electric Power Corporation (KEPCO). The data distinguished between FIT installations and RPS installations, which was considered in calculation of indemnity for each city. Table 1 summarizes the cost assumptions and installation for frequency and severity estimation.

(Equation 7)

$$\text{If } \left(\text{Sunshine Shortage}_i^k / \overline{\text{city's sunshine duration}}_i^k\right) > 0.1 \quad (or\ 0.2\ for\ scenario\ 2)$$

Where $\text{Sunshine Shortage}_i^k$ is the sunshine duration for city i in year k;

For $i = 1, \ldots, N$

$\overline{\text{city's sunshine duration}}_i^k$ is the average sunshine duration for city i in year k

$$\text{Minimum Revenue}_i^k = (\text{preceding } 10\,\text{year } \overline{\text{sunshine duration}}_i^k) * 365(\text{days}/\text{year}) * (\text{FIT installations}(kw)$$

$$* \text{FIT compensation}(KRW/kwh)) * \text{RPS installations}(kw) * \text{RPS compensation}(KRW/kwh))$$

$$k^{th}\ \text{year}(\text{shortage event severity}) = (\text{Sunshine Shortage}/\overline{\text{city}_i\text{'s sunshine duration}}) * (\text{Minimum Revenue})$$

The paper assumes that all of the analyzed installations renewed insurance contract for every year from 1990 until year 2015. It assumes that none of the parties terminated the contract during that period. This assumption is essential to analyze the distribution and frequency losses with only sunshine duration changing and all other variables held constant. The assumption of constant REC is also considered for the scenario when REC is included.

Location	FIT Installations (KW)	RPS Installations (KW)	Subsidy for FIT Installations KRW/KWh (2015 average)	SMP KRW/KWh (2015 average)	SMP+REC KRW/KWh (2015 average)
Kangnung	3806.2	8228.21	611.5	102.3212251	203
Goje	19.2	545.84	611.5	156.5868782	258
Gochang_gun	1961.12	15911.985	611.5	156.5868782	258
Gochang	23343.75	93447.71	611.5	172.1669216	273
Gwangju	203.6	4027.53	611.5	102.1620603	203
Gumi	1616.42	11856.245	611.5	102.124695	203
Gunsan	496.37	63816.355	611.5	121.5975539	223
Geumsan_gun	1139.32	5289.065	611.5	102.2054316	203
Namwon	8054.64	54263.25	611.5	121.5975539	223
Namhae_gun	522.8	1739.55	611.5	156.5868782	258
Daegu	542.51	31361.665	611.5	102.0693734	203
Daejon	336.63	12615.01	611.5	102.1463829	203
Mokpo	196.03	4668.52	611.5	172.1669216	273
Mungyong	4496	6378.77	611.5	102.124695	203
Milyang	4216.76	4390.78	611.5	156.5868782	258
Boryong	1645.12	22611.035	611.5	102.2054316	203
Boeun_gun	400.02	9698.865	611.5	102.1901663	203
Buan_gun	8329.29	23897.52	611.5	101.9625083	203
Busan	948.71	62166.005	611.5	121.5975539	223
Buyeo_gun	2925.55	23113.665	611.5	102.2054316	203
Sancheong_gun	2089.07	11397.05	611.5	156.5868782	258
Seogwipo	4137.36	48362.83	611.5	123.8592713	225
Seosan	1383.16	40907.065	611.5	102.2054316	203
Seoul	494.49	22826.83	611.5	102.9730276	204
Sokcho	19.8	1691.78	611.5	102.3212251	203
Suwon	32	1415.04	611.5	102.3574067	203
Yangpyong_gun	29.4	2426.995	611.5	102.3574067	203
Yeosu	698.33	7940.065	611.5	172.1669216	273
Yeongdeok_gun	10362.35	2705.67	611.5	102.124695	203
Yeongju	22387.79	21199.31	611.5	102.124695	203
Yongcheon	6265.92	16726.655	611.5	102.124695	203
Wando_gun	28.8	43379.13	611.5	172.1669216	273
Ulsan	453.68	9248.43	611.5	101.9537074	203
Uljin_gun	996.8	593.225	611.5	102.124695	203
Wonju	147.4	5818.435	611.5	102.3212251	203
Uiseong_gun	14221.76	14550.905	611.5	102.124695	203
Icheon	38.4	26627.43	611.5	102.3574067	203
Injae	328.02	4229.8	611.5	102.3212251	203
Incheon	1414.72	21731.217	611.5	102.3987252	204
Imsil_gun	3665.73	30994.745	611.5	121.5975539	223
Jangheung_gun	7812.75	9794.685	611.5	172.1669216	273
Jeonju	2961.54	19288.69	611.5	121.5975534	223
Jeongeup	17049.26	83005.935	611.5	121.5975539	223
Jeju	1159.81	21263.085	611.5	123.8592713	225
Jecheon	1035.92	7745.835	611.5	102.1901663	203
Jinju	2763.76	16766.195	611.5	156.5868782	258
Cheongju	352.85	12731.41	611.5	102.1901663	203
Chuncheon	330.83	11125.395	611.5	102.3212251	203
Chungju	272.04	11849.402	611.5	102.1901663	203
Tongyeong	0	351.44	611.5	156.5868782	258
Pohang	1473.47	12918	611.5	102.124695	203
Hapcheon_gun	5760.42	10074.82	611.5	156.5868782	258
Haenam_gun	17000.39	105709.11	611.5	172.1669216	273
Hongcheon_gun	201.68	5083.425	611.5	102.3212251	203

Table 1. <Electricity Cost and Installations by City>

Source: Korea Power Exchange (KPX) for SMP price, MOTIE (2014) for FIT price

5.2 Data

Before considering loss probability and severity, the following Box-plot will give the sense of the general variability in sunshine duration across time and space. The variance for historical sunshine duration spanned from 0.152 for Mokpo to 1.011 for Jecheon, whereas the average sunshine hours was in the range from 5.0073 for Jeju to 6.4742 for Yeondeok-gun.

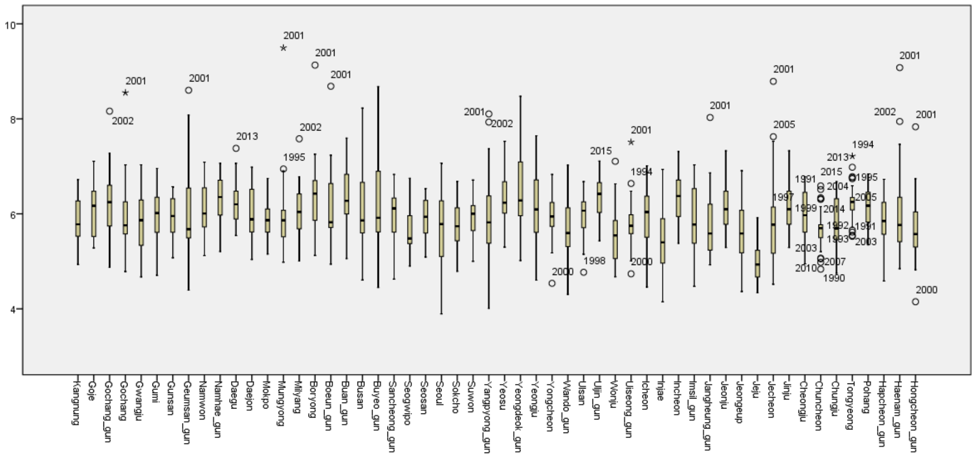

Figure 2. <Sunshine Duration Box Plot by City for period 1990~2015>

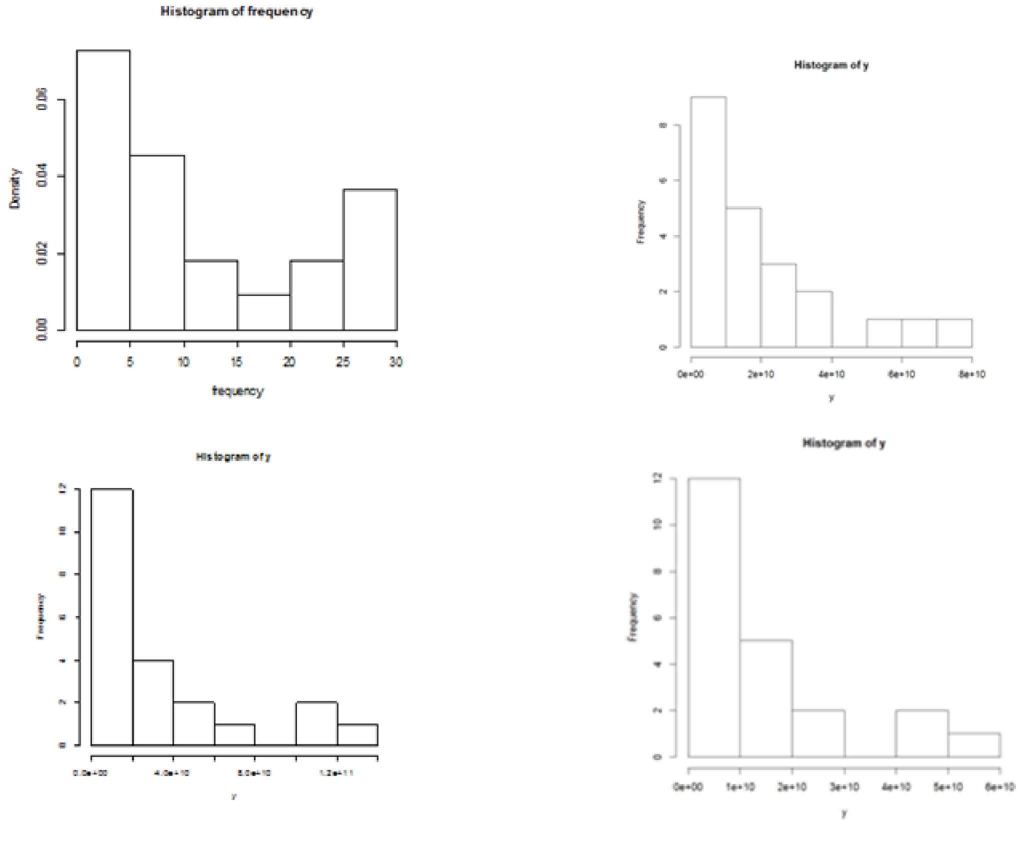

Figure 3. <Frequency and Severity Histograms, <10% shortfall >[3]

The frequency and the severity of the events are summarized in the histograms.

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[3] y denotes sunshine shortage severity in the graph

The information above indicates that there was no sunshine shortfall at any city in years 1997, 2004, 2013 and 2014. The column REC excluded indicates the loss severity information for the case when the sunshine shortfall insurance considers the SMP price as the sole source of solar developers. While this assumption in itself is not very realistic, it well describes the current solar insurance scheme sold in Korean markets. This simplification is further necessary if we are looking to describe only one source of risk – sunshine duration. On the other hand, the right hand column indicates solar insurance shortage in case REC is included. The frequency and severity graphs indicate the skewness of the data. The frequency and severity data (under various assumptions) both exhibit tails on the right, meaning they are positively skewed. This justifies more precise estimation of parameters, such as MLE and Bayesian approach. If the data followed normal distribution, there would be no need for these elaborate estimation techniques.

Year	Frequency	Severity (REC excluded)	Severity (REC included)
1990	24	12,497,868,325	30,860,453,322
1991	5	4,417,257,946	9,369,970,515
1992	9	5,583,489,976	19,227,533,729
1993	30	49,526,864,024	112,746,471,499
1994	5	4,679,578,031	11,885,168,450
1995	4	3,417,370,532	9,627,018,445
1996	11	15,267,896,883	35,408,128,185
1997	0	0	0
1998	29	46,117,133,670	101,836,691,246
1999	5	6,698,924,413	14,443,800,886
2000	30	51,731,068,476	120,040,311,841
2001	4	2,424,034,778	5,872,007,323
2002	8	8,670,630,355	18,813,265,198
2003	25	19,935,334,677	45,237,449,787
2004	0	0	0
2005	1	613,594,917	1,386,909,797
2006	10	5,416,770,049	13,095,097,897
2007	27	29,416,909,270	67,198,269,752
2008	9	10,531,399,556	21,101,530,991
2009	6	7,052,089,385	13,504,075,872
2010	19	25,357,239,101	54,958,090,197
2011	13	15,194,203,313	33,960,216,477
2012	3	6,720,013,432	13,160,017,289
2013	0	0	0
2014	0	0	0
2015	1	3,199,748,402	7,604,055,314

Table 2. <Frequency and Severity Data, <10% shortfall >

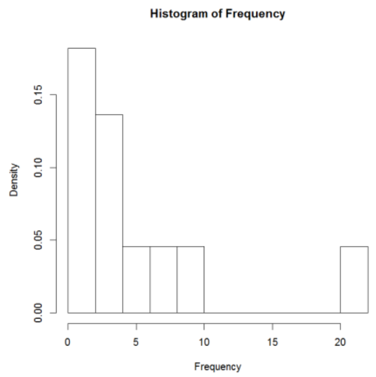


Figure 4.<Frequency and Severity Histograms, < 20% shortfall>

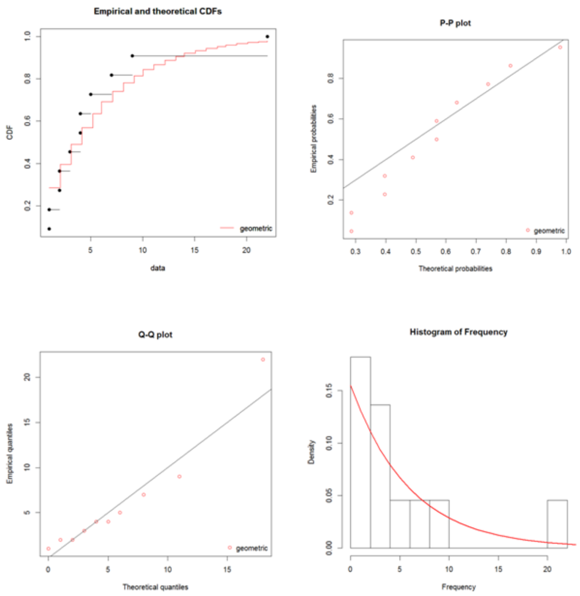
Only 11 out of 26 years demonstrated loss of sunshine below 80% level when compared to the past 10 year average. Year 2000 experienced systematic risk of sunshine that influenced 22 cities out of 54 cities. The second most affected year was 1993 with 9 cities experiencing loss of sunshine below the 80% level. However, the rest of the years had on average only 3.2 cities with sunshine loss below the 80% level. That is quite different from the case of frequency below 90% of historical average, when the average number of cities that experience sunshine loss (excluding most frequent 2 years) is 10.9. If we set the insurance product in such way that loss occurs only when sunshine shortfall is over 20% (in other words, when sunshine is below the 80% level), then we can no longer fit the data to Negative binomial distribution. Furthermore, Poisson distribution fits only in terms of central location of the frequency, i.e. according for K-S test, and does not fit for the tail distribution, i.e. according to A-D test. The only discrete probability distribution that fits based on both tests is geometric distribution. Below is the summary of the parameters.

distribution	Probability Mass Function	Parameters
geometric	$(1-p)^{k-1}p$	p=0.1549296

<Frequency Parameters for Geometric Distribution, <20% shortfall>

distribution	K-S test		A-D test	
geometric	Statistic	p-value	Statistic	p-value
	0.28586	0.3299	0.84206	0.4487

<Geometric Distribution Test Statistics, <20% shortfall >



<Fit of Frequency Data for Geometric Distribution, <20% shortfall >

Interestingly enough, shortfall below 40% of the directly preceding 10 year average did not occur at all. Furthermore, the instances of sunshine shortfall below 30% of the preceding 10 year average is extremely rare and therefore was not even considered in this paper.

6. Parameter Estimation for 10% Shortage Scenario

6.1 Frequency

6.1.1 MLE Estimation of Frequency

This paper tested for discrete distributions and their fit for the frequency data. Only the distributions that passed the KS test, AD test and matched the QQ and PP plot well are presented in this paper. Although theoretically Poisson distribution fits well for the count data, KS test's and AD test's p-values were below 0.05 level. Uniform distribution was not supported by the KS and AD test either. The significance value for KS test and AD test can be confusing since the lower it is, the lower there is a chance that the data comes from the evaluated distribution. In other words, the larger the p-value is, the higher the chance to support our hypothesis.

The null hypothesis for KS and AD tests is that the proposed distribution and actual data fit the same distribution. Therefore, if we encounter a p-value for these tests below the 5% level, it indicates that there is less than 5% chance that the proposed distribution matches the actual distribution of a data. As a result, we are forced to reject the null hypothesis of homogeneity of distributions and conclude that the data matches another distribution better. Similarly, if the points on the PP plot and QQ plot deviate significantly from the 45 degree line, we should conclude that the data does not match the suggested distribution well. The only discrete distribution that was statistically significantly supported by the KS test, AD test and by plotting the data, was negative binomial distribution. The result of the tests for negative binomial distribution is summarized below.

distribution	K-S test		A-D test	
	Statistic	p-value	Statistic	p-value
negative binomial	0.14905	0.7127	0.55482	0.6897

Table 3. <Negative Binomial Distribution Test Statistic>

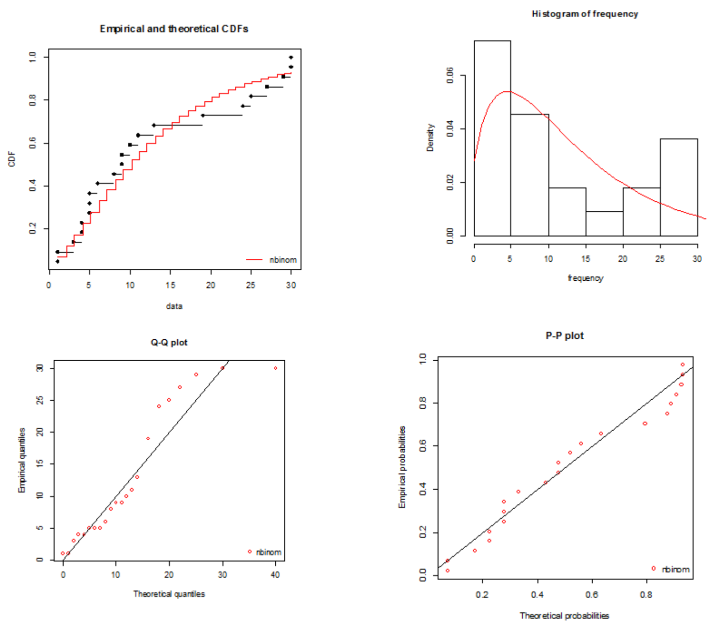


Figure 5. <Fit of Frequency Data for Negative Binomial Distribution>

Further, the paper presents PP plot, QQ plot, cumulative distribution function and how well the actual data matches the frequency (binomial distribution line plotted in a histogram). As is evident from the graphics, actual data's cumulative distribution points are not far away from the negative binomial distribution points. Despite a few points where the data deviates from PP plot and QQ plot, in general the data follows the 45 degree line. The data is positively skewed, which makes is a good fit for negative binomial distribution as is clear from the fitted line on the histogram.

Considering a good fit, this paper estimated the parameters of negative binomial distribution using MLE estimation. The result is summarized in table 4 below.

distribution	Probability Mass Function	Parameters
negative binomial	${}_{k+n-1}C_k \cdot (1-p)^n p^k$	n=1.6537
		p=0.1157

Table 4. <Frequency Parameters for Negative Binomial Distribution>

6.1.1 Bayesian Estimation of Frequency

The choice of distribution for parameter n was particularly challenging. All of the available information is that the values *n* should follow a continuous non-negative distribution. Following Professor John K. Kruschke of Psychological and Brain Sciences in Indiana University, the author of "Doing Bayesian Data Analysis", this paper chose gamma distribution with the essentially non-informative parameters (0.01, 0.01) to avoid bias in calculations. John D. Cook(2009) specifies that p should follow beta prior. Similarly, due to the insufficient information about the original shape of beta prior, this paper will use the most general form. To summarize, priors for the two parameters in this paper will be given as n ~ dgamma(0.01,0.01) and p ~ dbeta(1,1). To estimate the values, I used fouchains simultaneously simulating the values. The autocorrelation plot provides information about convergence of values and mixing of the chains. As we see, the autocorrelation almost disappears by the end of the simulation process. The mean estimate of p from Bayesian analysis was 0.1246 (s.d. 0.3987), while n was 1.7864 (s.d. 0.6959).

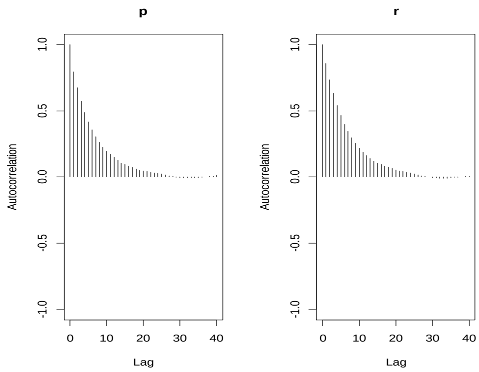


Figure 6. <Autocorrelation Plot>

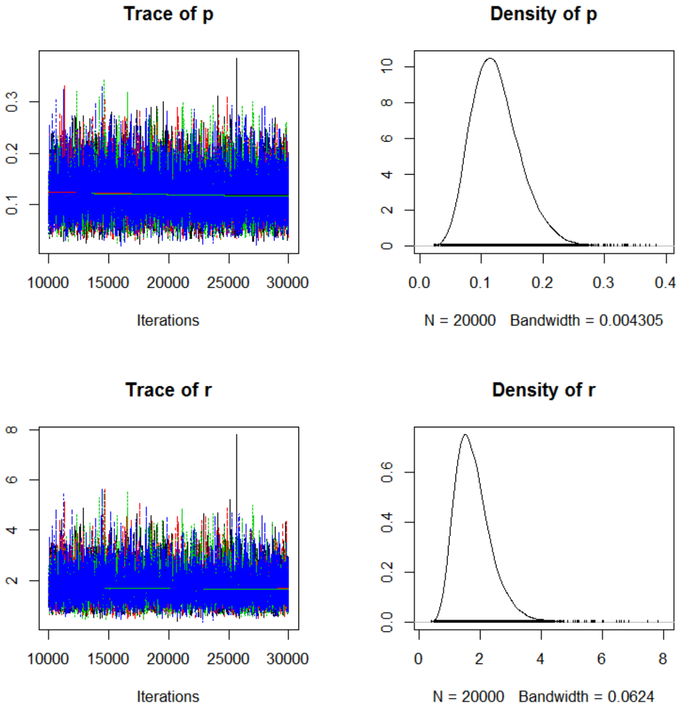


Figure 7. <Bayesian Simulation[4]>

The simulation outcome below indicates that both p and r are convergent to one number. Next, the autocorrelation plot indicates that the convergence is fast and consistent since it virtually approaches to zero.

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[4] *r* in the graph corresponds to *n* in the output interpretation part

6.2 Severity

6.2.1 MLE Estimation of Severity

The last and the most suitable distribution for severity data is lognormal distribution. Judging from the KS test and AD test p-value, there is very little chance that when a value is randomly selected from the severity data will not fit the normal distribution. Table 5 summarizes KS and AD test statistics, whereas table 6 introduces the parameters that were calculated using the maximum likelihood estimate in R program. Unfortunately the singularity and scaling of the distribution prevented from applying Weibull or Generalized Extreme Value to estimate the parameters.

distribution	K-S test		A-D test	
	Statistic	p-value	Statistic	p-value
lognormal	0.09744	0.9718	0.23763	0.9765

Table 5. <Lognormal Distribution Test Statistics>

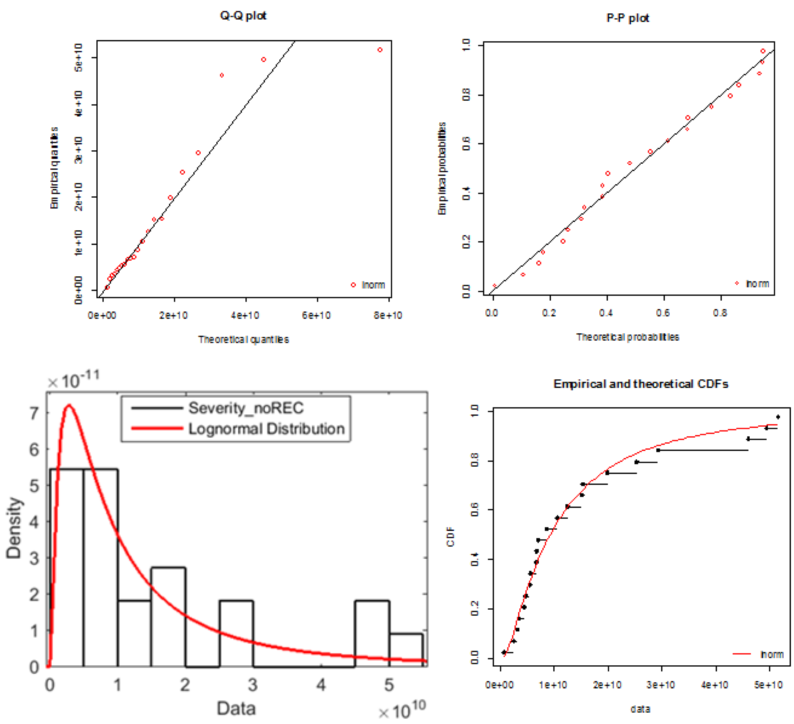


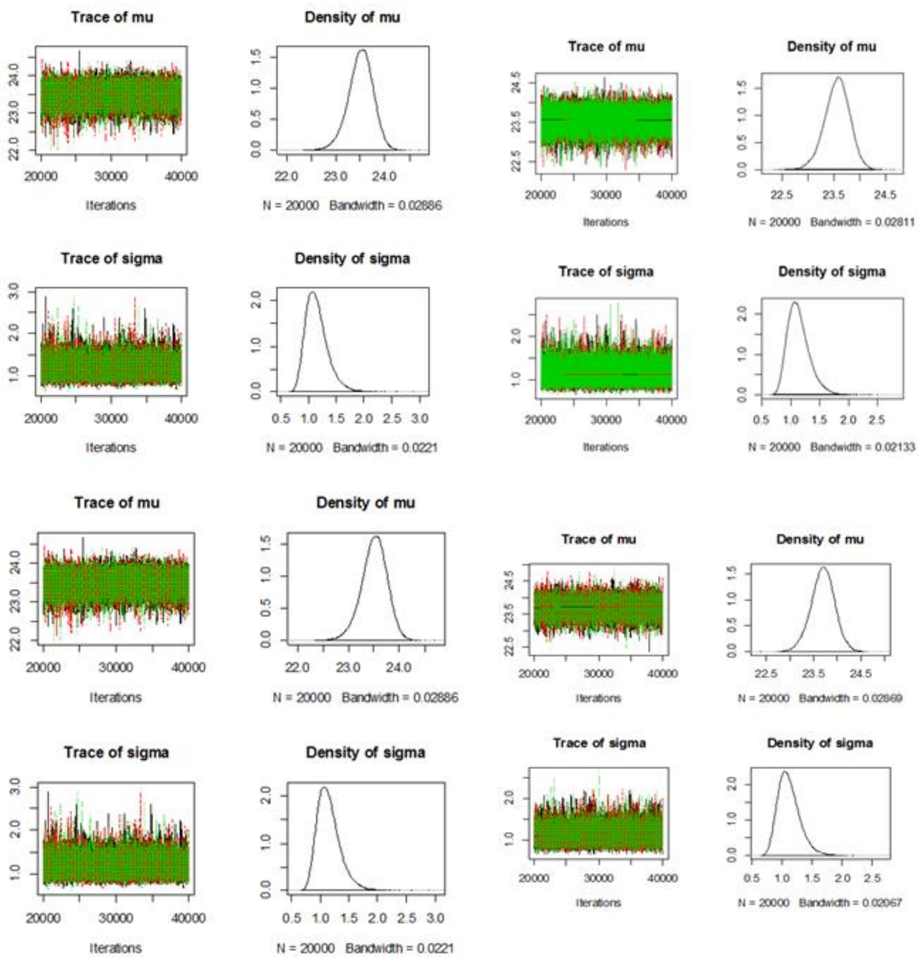
Figure 8. <Fit of Severity Data for Lognormal Distribution>

distribution	Probability Mass Function	Parameters
lognormal	$\mathcal{N}(\ln x;\mu,\sigma)=\frac{1}{\sigma\sqrt{2\pi}}\exp\left[-\frac{(\ln x-\mu)^2}{2\sigma^2}\right]$	μ=22.9397
		σ= 1.0664

Table 6. <Lognormal Distribution Parameters>

6.2.2 Bayesian Estimation of Severity

There are four different distribution cases, i.e. Bayesian severity parameter estimation with changing base year and no RECs, Bayesian severity parameter estimation with changing base year and including RECs, Bayesian severity parameter estimation with fixed base year and no RECs, and finally Bayesian severity parameter estimation with fixed base year and including RECs. The summary of the simulation is presented below while the simulation output will be organized and compared in the next section. The autocorrelation plot approached to zero indicating convergence.



Severity Distribution Parameters by Lognormal MLE Estimation								
Year	Excluding REC, changing base year		Including REC, changing base year		Excluding REC, fixed base year		Including REC, fixed base year	
	μ_t	σ_t	μ_t	σ_t	μ_t	σ_t	μ_t	σ_t
1990	19.6783	1.01585	20.5355	1.03254	19.6783	1.01585	20.5355	1.03254
1991	19.6098	2.06708	20.386	2.18983	19.6894	2.08638	20.386	2.18983
1992	19.6617	1.15148	20.6429	1.369	19.8253	1.15724	20.6429	1.369
1993	19.8652	1.2045	20.8712	1.0923	19.941	1.8283	21.3201	1.2731
1994	19.0412	2.16651	21.2754	1.4611	20.4396	1.32496	21.2132	1.39317
1995	20.3327	1.3625	21.2756	1.36913	20.6707	1.0078	21.205	1.14104
1996	20.3187	1.06924	21.2132	1.39317	20.6965	1.14846	21.2062	1.28449
1997	No Sunshine Shortfall							
1998	20.4296	1.36134	21.3917	1.34333	20.6995	1.46168	21.2754	1.4611
1999	20.2854	1.49949	20.7333	1.08226	20.7252	1.29926	21.2756	1.36913
2000	20.4296	1.36134	21.0513	1.04363	21.1582	1.04647	21.2132	1.39317
2001	19.8969	0.848975	20.5807	1.40544	20.7608	1.33778	21.3917	1.34333
2002	20.5058	1.30331	20.2779	1.42707	20.0645	1.05862	20.7333	1.08226
2003	19.8969	1.00276	21.032	1.1751	20.504	1.21092	21.0513	1.04363
2004	No Sunshine Shortfall							
2005	Lack of Observations to Estimate Parameters							
2006	Lack of Observations to Estimate Parameters							
2007	20.2238	1.05762	20.6109	1.32625	19.8401	1.53881	20.5807	1.40544
2008	19.7518	1.36672	20.2019	1.54801	19.4684	1.74518	20.2779	1.42707
2009	19.3432	1.46667	21.0114	1.41114	20.5383	1.34178	21.032	1.1751
2010	20.1639	1.13425	20.7494	1.6229	19.9432	1.41854	20.6109	1.32625
2011	19.7868	1.36676	20.3268	1.3329	19.5576	1.54633	20.2019	1.54801
2012	19.4001	1.61653	21.0045	1.2643	20.4393	1.14307	21.0114	1.41114
2013	No Sunshine Shortfall							
2014	No Sunshine Shortfall							
2015	Lack of Observations to Estimate Parameters							

Table 7. <Severity Distribution Parameters by Lognormal MLE Estimation>

To take advantage of the extra information available from Bayesian approach, this paper estimated the prior distribution parameters based on the movement of mu and sigma inside each year when fit for lognormal distribution. All of the parameters were statistically fit based on K-S test and A-D test. The information in table 7 was used to create JAGS code. u_t in each column was also fit to normal distribution to obtain the general mean value. sigma $_t$ on the other hand was not directly used to estimate the variance between years, since the only information that can be used from table 7 about the variance is the dispersion of u within each year (not between years). Hence sigma was given non-informative prior, i.e. gamma distribution with parameters (0.01, 0.01).

In some years, specifically in year 1997, 2004, 2013 and 2014, no city experienced sunshine duration shortfall since all cities were above the historical average. In 2005 and 2006, the number of cities that were below the historical averages was 3 or less, rendering MLE estimation absolute. Agreeably, more samples would make results more reliable. However, the observed estimations will not be used as indicators of yearly shortfalls. They are merely used as a reference to track the distribution of mean log and standard deviation log which conceive information for appropriate prior distribution selection. From the probability distribution of the data in the table above, μ_t and σ_t each follow Normal and Gamma distributions. The shape data for μ_t leaves little doubt about the Normality of the distribution. Similarly, Gamma distribution does not only follow the shape well but is also conventionally used for standard deviation priors. The estimated parameters for μt and σt are given as to specify prior distribution, whereas the aggregate distribution of loss severity data is input in the model as likelihood. In order to observe if the mixing within chains and convergence are quick, I observed autocorrelation plot below (which demonstrates one chain as an example). A is evident from the graph autocorrelation virtually vanishes after a few simulations. Much Burnin in the beginning of the simulation can the model to "forget" its initial values. This paper used MLE estimation for parameters of mu and sigma, so setting these initial values was deemed valuable sources of information. As a result, this paper did not include Burnin in the model. The final results for all distributions are organized in the next section.

6.3 Parameter Estimation Summary

Table 8 presents the summary of parameters for different output combinations. The results for Bayesian and MLE approach appear quite similar. In fact, the difference in mean of the lognormal distribution between MLE and Bayesian estimation is just 0.03. The largest difference for estimation of mean between MLE and Bayesian approach is 0.23, which is still quite similar. Theoretically, there is no reason to say that either MLE or Bayesian approach is more precise. The two estimation models are different. However, if the difference between the estimations is significant, there is a chance that one of the models was not right. Here, on the contrary, all parameters are very similar, which proves that the estimations are trustworthy.

Distribution	Estimation Method	Parameters' name	Parameters' value (with changing base year)	Parameters (with base year fixed at year 1990)
Severity (REC excluded)	MLE	meanlog (sdlog)	22.9397 (1.09145)	24.1281324 (0.7422268)
	Bayesian	meanlog (sdlog)	22.9 (1.133)	24.0022 (0.7913)
Severity (REC included)	MLE	meanlog (sdlog)	23.775554(1.050861)	24.9717744 (0.7121249)
	Bayesian	meanlog (sdlog)	24.0237(0.7883)	24.8495 (0.7601)
Frequency	MLE	n (p)	1.6537 (0.1157)	
	Bayesian	n (p)	1.7864 (0.1246)	

Table 8. <Parameter Estimation Comparison>

Based on the estimated parameters, this paper analyzed the aggregate using 'actur' (actuarial package) in R. To implement the simulation using this package, it was necessary to obtain lognormal distribution for each case as summarized above.

7. Value at Risk Estimation Using LDA

7.1 VaR Summary

The convolution of the frequency and severity distribution to obtain aggregate loss distribution was performed through 10,000 simulations 30 times for each combination. (Table 9). The averages of 30 times of LDA simulations are summarized in table 9. Appendix A provides more detailed output of LDA simulation. The first interesting observation is that the "climate change effect" results into risk premium of as small as 23,018,8000 to large as 1,020,404,538,780, a significant difference.

<LDA Output Negative Binomial-LogNormal Distribution Combination> (Unit: million KRW)							
Assumptions	Estimation Method	50%	75%	90%	95%	99%	99.9%
REC excluded, changing base year	MLE	159,503,620,309	297,219,858,995	455,324,223,333	577,076,050,000	856,246,960,000	1,258,432,566,667
	Bayesian	158,786,300,000	296,104,600,000	474,357,640,000	604,100,670,000	905,835,010,000	1,350,744,300,000
REC included, changing base year	MLE	343,406,200,000	635,457,700,000	1,028,058,200,000	1,302,996,200,000	1,925,269,800,000	2,776,207,000,000
	Bayesian	295,313,800,000	555,764,100,000	903,728,226,667	1,147,702,133,333	1,714,597,166,667	2,508,651,000,000
<LDA Output Negative Binomial-LogNormal Distribution Combination> (Unit: million KRW)							
Distribution	Estimation Method	50%	75%	90%	95%	99%	99.9%
REC excluded, fixed base year	MLE	390,290,100,000	693,265,900,000	1,041,732,870,968	1,304,042,387,097	1,893,411,096,774	2,684,245,419,355
	Bayesian	368,763,300,000	643,950,800,000	936,500,538,710	1,167,988,677,419	1,682,374,322,581	2,391,987,354,839
REC included, fixed base year	MLE	894,223,000,000	1,590,537,000,000	2,452,671,533,333	3,071,704,466,667	4,441,316,700,000	6,302,892,733,333
	Bayesian	839,147,400,000	1,477,347,000,000	2,192,606,700,000	2,730,395,900,000	3,942,324,700,000	5,618,116,700,000

Table 9. <LDA Simulation Output>

<Risk per KW> (Unit: million KRW/KW)							
Assumptions	Estimation Method	50%	75%	90%	95%	99%	99.9%
REC excluded, changing base	MLE	121,288	226,009	346,234	438,815	651,100	956,927
	Bayesian	120,743	225,161	360,707	459,365	688,807	1,027,122
REC included, changing base	MLE	261,130	483,209	781,747	990,813	1,463,997	2,111,060
	Bayesian	224,560	422,609	687,205	872,726	1,303,799	1,907,607

<Risk per KW> (Unit: million KRW/KW)							
Distribution	Estimation Method	50%	75%	90%	95%	99%	99.9%
REC excluded,	MLE	296,781	527,167	792,146	991,609	1,439,772	2,041,131
fixed base year	Bayesian	280,412	489,668	712,126	888,152	1,279,297	1,818,895
REC excluded,	MLE	679,977	1,209,463	1,865,040	2,335,760	3,377,228	4,792,792
fixed base year	Bayesian	638,097	1,123,392	1,667,283	2,076,225	2,997,789	4,272,081

Table 10. <LDA Simulation Output per KW>

Tables 9 represents VaR values for changing and fixed base year, each. First, it is easy to see that the risk is considerable. For the 99% level, the estimated risk reaches over KRW 1 trillion for cases that do not include RECs and over KRW 3 trillion for cases that do. This does not seem natural, especially considering that Tables 11 and 12 show this value is even higher than the insured value (revenue) that a solar developer is projected to earn on average. Therefore, a more realistic estimation of risk would be 75%~90% of the risk. However, even if an insurance company decides to set premiums for risk at these percentiles, it is still unacceptable for solar developers, who, for sure would not want to give half of their earned income to the insurance company. NREL (2010) suggested that 20~25% of operational maintenance cost is used for insurance. However, the calculations here indicate that estimated risk at 50% is as high as 50% of the solar developers' income. Moreover, if we consider that including RECs is a more realistic representation of the solar developers' reality, then the risk proportion of insured value climbs as high as 40~47% for the 50th percentile of expected risk. Perhaps the reason why solar insurance providers do not include RECs is not just because its value is hard to predict, but because even taking RECs at their face average values, the risk is excessively high. In other words, when RECs are included, the solar development company should allocate twice as high amount of money on unexpected sunshine shortfall and solar developers will need to bear twice the risk.

<Risk Proportion of Insured Value>							
Assumptions	Estimation Method	50%	75%	90%	95%	99%	99.9%
REC excluded,	MLE	0.22	0.40	0.62	0.78	1.16	1.71
changing base year	Bayesian	0.22	0.40	0.64	0.82	1.23	1.83
REC included,	MLE	0.47	0.86	1.39	1.77	2.61	3.76
changing base year	Bayesian	0.40	0.75	1.22	1.56	2.32	3.40

Table 11. <Risk Proportion of Insured Value>

<Risk Proportion of Insured Value >							
Distribution	Estimation Method	50%	75%	90%	95%	99%	99.9%
REC excluded, fixed	MLE	0.53	0.94	1.41	1.77	2.57	3.64
base year	Bayesian	0.50	0.87	1.27	1.58	2.28	3.24
REC included, fixed	MLE	1.21	2.16	3.32	4.16	6.02	8.54
base year	Bayesian	1.14	2.00	2.97	3.70	5.34	7.62

Table 12. <Risk Proportion of Insured Value per KW>

Year	Estimated Yearly Revenue for 54 cities
1,990	839,295,195,102
1,991	782,050,045,583
1,992	783,605,933,624
1,993	677,364,664,533
1,994	804,681,103,547
1,995	785,224,239,065
1,996	740,266,004,124
1,997	771,009,848,677
1,998	659,092,501,194
1,999	717,615,272,663
2,000	627,063,515,157
2,001	873,426,480,162
2,002	773,028,364,531
2,003	707,105,993,978
2,004	789,005,957,820
2,005	769,233,589,403
2,006	709,823,719,406
2,007	653,669,997,912
2,008	698,419,493,815
2,009	708,389,163,547
2,010	655,763,697,864
2,011	689,366,955,634
2,012	718,857,581,834
2,013	781,770,402,762
2,014	732,572,816,781
2,015	733,816,224,703
Average	737,750,721,670

Table 13. <Yearly Aggregate Revenues for 54 Cities>

This paper considered both Bayesian and MLE estimation for maximum probable loss due to sunshine duration shortfall. However, much of the information that Bayesian approach used as inputs was built based on MLE estimation of the parameters. This was inevitable since there is very limited research on the solar insurance, especially in Korea. Consequently, the Bayesian approach required much lengthier preparation, such as model building, parameter selection and actual simulation. On the other hand, when the subject is intensively research and MLE estimation is virtually impossible, Bayesian approach can be an extremely insightful and time-saving tool.

Based on the estimation of the losses through LDA, it is clear that the risk of sunshine shortfall is high and could potentially result in billion KRW of losses. That could partially explain why Korean insurance companies hesitate to promote this type of insurance. The severity of risk matches both the normally distributed and extreme events making it challenging to comprehend the type of risk. In addition, the risk frequency indicates that some years have just a few cities that experience sunshine shortfall and the proposed definition, whereas in other times almost every city is exposed to such risk. However, the correlation is not evident either - sunshine shortfall in not a ubiquitous event equally affecting each city. That is probably why insurance companies are forced to charge high fees for this types of insurance. Though the study did indicate that solar developers could save a lot in losses due to sunshine shortfall, an individual insurance company would be more interested in issuing derivatives or other investable instruments as opposed to insurance; partially due to lack of demand.

7.2 Interpretation

The tricky question remains to translate the numbers from aggregate risk of Loss Distribution Approach to insurance premiums. Unfortunately, I did not have access to risk valuation tools used in an insurance company and therefore I can only provide the general intuition in this paper. Table 14 was calculated based on the premise that business interruption companies usually charge 50%[5] as premium to their customers (although the range may be between 30~150%). In other words, Loss ratio=(50th Percentile Aggregate Loss)/Gross Premium. Here gross premium means the premium charged to consumers and is the sum of net premium and premium loading. In case the loss is less than 100%, insurance companies make profit. However, if the loss ratio is above 100%, it implies that insurance companies compensate more than they receive. In case of some extreme loss scenario that can happen in storm and flood insurance indemnity cases, the insurance company would pay up to 180% of expected losses, whereas the government would cover the rest.[6] Table 15, on the other hand, puts values into perspective by telling what the rough insurance premium will be with the simulated results. For instance, for a typical solar developer (100 KW in case of Korea), the person would have

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[5] Korea Insurance Consumer Federation (2008). “Base for Indemnity Insurance Premium”. Retrieved from http://kicf.egloos.com/m/10308542 on June 1st, 2016.

[6] Ministry of Public Safety and Security (2016). “풍수해보험사업 운영계획(안)” [2016 Storm and Flood Insurance Program]. 재난보험과, p.16

to pay from KRW 24,257,700 to KRW 44,912,000 without premium and from KRW 59,356,200 to 1,27,619,500 per year. Naturally, the acceptance of such arrangement would depend on a solar developer's resources, but it seems quite impossible to realize.

<Estimated Total Insurance Premium for 54 Cities> (Unit: million KRW)			
Assumptions	Estimation Method	Premium (changing base year)	Premium (fixed base year)
REC excluded, changing base year	MLE	319,007,240,618	780,580,200,000
	Bayesian	317,572,600,000	737,526,600,000
REC included, changing base year	MLE	686,812,400,000	1,788,446,000,000
	Bayesian	590,627,600,000	1,678,294,800,000

Table 14. <Aggregate Insurance Premium, loss ratio=50%>

<Estimated Insurance Premium per KW> (Unit: million KRW/KW)			
Assumptions	Estimation Method	Premium (changing base year)	Premium (fixed base year)
REC excluded, changing base year	MLE	242,577	593,562
	Bayesian	241,486	560,824
REC included, changing base year	MLE	522,260	1,359,955
	Bayesian	449,120	1,276,195

Table 15. < Insurance Premium per KW, loss ratio=50%>

However, insurance premium charged to consumers could be altered if insurance companies become willing to receive lower gains on insurance premiums. To accomplish this task, insurance companies will have to cut costs required to keep the insurance product running. To see how much the insurance companies in Korea are willing to lower their profit margins, this paper considered the minimum profit that insurance companies are willing to make. In the past, insurance companies in Korea expressed reluctance to enter the industry where the loss ratio of the previous 3 years exceeds 80%.[7] Therefore, this paper also examines the case of the maximum acceptable loss ratio equivalent to 80%. To assess the acceptability of the insurance premiums, they were estimated against the total fixed investment costs for the project, and the ratio in the average sales from electricity (including REC price). Since previous results showed that fixing the base year or including REC leads to higher premiums, this paper will consider if the lowest of the premiums (case of no RECs and changing base year) are acceptable. In fact, insurance costs would decrease from 6% to 4% of the total fixed costs, if

[7] KMA (2012). "A Study on the Feasibility of Introducing Weather Derivatives", Bgain(Inc.), p.87, http://img.kisti.re.kr/tr_img/2012215/rttrko000000150585.pdf

we consider fixed costs of the year 2010, and decrease from 12% to 8%, if we assume fixed costs of PV project for year 2015. That is still far higher than “0.25% to 0.5% of the total fixed cost” presented in NREL (2010). Similarly, the portion of insurance fee in sales revenue would also decrease from 43% to 27%, depending on the loss ratio. However, that would still be much higher than “5% to 10% of the total cost of energy from installations” stated in NREL(2010).

<Estimated Total Insurance Premium for 54 Cities> (Unit: million KRW)		
Assumptions	Estimation Method	Premium (changing base year)
REC excluded,	MLE	199,379,525,386
	Bayesian	198,482,875,000
REC included, changing base year	MLE	429,257,750,000
	Bayesian	369,142,250,000

Table 16. <Aggregate Insurance Premium, loss ratio=80%>

<Estimated Insurance Premium per KW> (Unit: million KRW/KW)		
Assumptions	Estimation Method	Premium (changing base year)
REC excluded,	MLE	151,610
	Bayesian	150,929
REC included, changing base year	MLE	326,413
	Bayesian	280,700

Table 17. < Insurance Premium per KW, loss ratio=80%>

The results above motivated the analysis of additional cases: when insurance is covered only in cases of sunshine duration below the 20% of historic average. (Table 18~table 24). In such case, if insurance is calculated based on 50% loss ratio, insurance premium will constitute 1% of the fixed costs (2010 fixed cost based), and 2.1% for the fixed costs for 2015 fixed cost estimation. This is still high but might be acceptable by some. Furthermore, the insurance cost portion in the average cost of electricity generation falls to 7.2%~ 7.4% thresholds, which is the realistic number based on NREL (2010). Finally, when we consider 80% loss ratio under this scenario, even the fixed cost drops to rather realistic level of 0.6% for fixed costs of 2010 and 1.3% of 2015. The ratio of insurance to energy sales becomes around 4.5% which is even lower than NREL (2010) presented in the report. Consequently, the marketable insurance is the one when solar companies cover sunshine loss below 20% of the historic average, and require only 20% or less to cover their profits.

<Estimated Total Insurance Premium for 54 Cities> (Unit: million KRW)		
Assumptions	Estimation Method	Premium (changing base year)
REC excluded, changing base year	MLE	54,654,038,910
	Bayesian	53,236,816,996

Table 18. <Aggregate Insurance Premium, loss ratio=50%>

<Estimated Insurance Premium per KW> (Unit: million KRW/KW)		
Assumptions	Estimation Method	Premium (changing base year)
REC excluded,	MLE	41,560
	Bayesian	40,482

Table 19. < Insurance Premium per KW, loss ratio=50%>

<Estimated Total Insurance Premium for 54 Cities> (Unit: million KRW)		
Assumptions	Estimation Method	Premium (changing base year)
REC excluded,	MLE	34,158,774,319
	Bayesian	33,273,010,623

Table 20. <Aggregate Insurance Premium, loss ratio=80%, changing base year, <20% shortfall >

<Estimated Insurance Premium per KW> (Unit: million KRW/KW)		
Assumptions	Estimation Method	Premium (changing base year)
REC excluded,	MLE	25,975
	Bayesian	25,301

Table 21. < Insurance Premium per KW, loss ratio=80%, changing base year, <20% shortfall>

In the end, this paper is a roadmap for insurance companies and solar developers who want to deal with sunshine shortfall risk. It considered important issues and most realistic scenarios of structuring insurance payment and the associated risk. In the end, the implementation of the insurance will depend on the financial situation of the insurance company as a whole or the related business division in particular. The choice to enter this type of business interruption insurance will rest on the amount of dispensable assents and risk-tolerance of the insurance company. As a result, it is not clear if at least some insurance companies would be interested in entering sunshine duration insurance despite of its high risk.

8. Research Significance and Limitations

8.1 Research Significance

The issue of sunshine-based weather insurance and the estimation of risk was not addressed either in domestic or foreign literature. Therefore, this study will be the crucial stepping stone for the future development in the field of weather risk literature. This paper can conclude in general that sunshine duration insurance presents too high of a risk to become commercially successful. The only possible approach would be to cover the damage of solar developers for very extreme risks, such as the sunshine shortfall less than 50% or more.

This paper introduced the issue of climate change into solar insurance topic. The implication of the results is that solar insurance providers will further increase the insurance premium on yearly basis. Otherwise, they will not be willing to provide insurance to customers with the fixed year, but would rather set insurance contracts to moving historical average. This sort of arrangement, on the other hand, would have an adverse impact on solar developers, who count on the similar sunshine duration performance for the projected 15~20 years of their PV facility. Due to more frequent and prolonged rainy seasons, reflecting climate change on the peninsula, sunshine duration is most likely to slowly decrease in the future.

From the insurer's perspective, long-term contracts are desirable, not only because of the high search and marketing cost, but also considering the fact that sunshine shortfall's volume and frequency is highly variable from year to year. As a result, the rates for insurance will have to be increased or the structure of the insurance product should follow the current structure in the market.

8.2 Limitations

Among the other assumptions, this paper viewed error in parameter estimation as constant. Further study might need to relax this assumption for a more precise estimation. Furthermore, due to the lack of actual data and the difficulty in their accessibility, this paper traced the solar shortfall based on the review of existing insurance agreements. This approach was deemed appropriate since the terms insurance payments were solely dependent on the variables that could be obtained through Korea Meteorology agency and Korea Energy Agency. If Korean solar insurance market grows in the future, the future task will be to evaluate how well the hypothetical sunshine shortfall matches the actual sunshine shortfall insurance claims in Korea.

Furthermore, this paper also did not assign different risks based on the geographical location within each city since privacy conditions prevent institutions like Korea Energy Agency from disclosing such personal information about individual solar developers. However, insurance companies that enter into contract with these solar developers could adjust the risk of individual solar developers based on the elevation, angle etc. Another limitation of this paper stems from the fact that it based calculation on the installations as of the end of December 31, the most currently available data. Similarly, it used REC and SMP as the average of year 2015 to match the installations.

Another issue that providers of sunshine duration insurance might want to include is the performance decline due to the aging of PV installations. NREL 2013 report suggests that US manufacturers usually offer performance guarantees of 90% of the optimal input for 10 years and 80% of the following `5 years of PV operating lifetime.

Finally, many firms provide all-in risk products which offer natural disasters, unexpected weather conditions and sunshine duration shortfall altogether. This paper analyzed sunshine duration risk separately since it is the most understudied area and occurs more regularly than the extreme weather events. A number of tools to predict catastrophic risks are already available in the market: Risk Management Solutions, AIR Worldwide, and EQECAT among others. However, the author of this paper is not aware of sunshine duration assessment tools, which made the subject even more attractive for research. Combining different type of risks with the appropriate weights enters the realm of insurance product development and therefore is not dealt with in this paper.

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Appendix

1.

Bayesian_withoutREC (changing base year)	<LDA Output Negative Binomial-LogNormal Distribution Combination>			
Simulation #	90.0%	95.0%	99.0%	99.9%
1	473,430,100,000	597,241,500,000	861,610,000,000	1,350,724,000,000
2	482,859,800,000	608,137,100,000	912,292,000,000	1,411,557,000,000
3	470,213,400,000	605,976,600,000	906,383,700,000	1,404,028,000,000
4	474,981,400,000	607,360,800,000	906,917,300,000	1,326,754,000,000
5	471,785,500,000	602,631,900,000	922,379,500,000	1,272,178,000,000
6	476,805,700,000	609,214,800,000	926,043,500,000	1,345,564,000,000
7	482,589,200,000	614,678,000,000	926,956,400,000	1,384,727,000,000
8	475,149,200,000	605,526,500,000	905,991,100,000	1,360,052,000,000
9	470,876,900,000	604,554,200,000	912,070,300,000	1,368,402,000,000
10	486,537,100,000	608,067,100,000	903,778,900,000	1,306,944,000,000
11	473,390,200,000	606,556,200,000	953,340,200,000	1,508,567,000,000
12	476,087,800,000	607,292,700,000	926,252,100,000	1,399,799,000,000
13	464,495,700,000	588,898,200,000	884,617,000,000	1,209,223,000,000
14	483,264,800,000	620,452,300,000	915,666,100,000	1,383,195,000,000
15	470,051,700,000	599,287,500,000	903,461,700,000	1,422,308,000,000
16	475,504,400,000	593,977,200,000	895,099,200,000	1,312,706,000,000
17	478,294,600,000	612,541,300,000	936,560,000,000	1,352,807,000,000
18	472,638,700,000	611,491,200,000	924,790,100,000	1,301,897,000,000
19	476,926,300,000	600,096,800,000	897,139,600,000	1,279,633,000,000
20	463,887,500,000	588,043,300,000	876,485,800,000	1,411,303,000,000
21	468,164,100,000	591,533,200,000	886,883,800,000	1,349,804,000,000
22	473,851,500,000	611,240,100,000	891,308,800,000	1,411,303,000,000
23	470,233,000,000	593,776,100,000	888,462,000,000	1,250,356,000,000
24	478,536,400,000	601,372,000,000	893,890,400,000	1,297,989,000,000
25	477,463,500,000	603,229,900,000	912,540,500,000	1,368,868,000,000
26	472,362,300,000	608,575,100,000	911,439,600,000	1,328,146,000,000
27	472,548,800,000	609,672,400,000	892,504,800,000	1,317,878,000,000
28	470,266,500,000	599,498,800,000	880,126,800,000	1,183,354,000,000
29	479,168,700,000	616,503,200,000	934,215,100,000	1,461,971,000,000
30	468,364,400,000	595,594,100,000	885,844,000,000	1,440,292,000,000
Average	**474,357,640,000**	**604,100,670,000**	**905,835,010,000**	**1,350,744,300,000**

2.

MLE_without REC (changing base year)	<LDA Output Negative Binomial-LogNormal Distribution Combination>			
Simulation #	90.0%	95.0%	99.0%	99.9%
1	454,983,500,000	572,347,200,000	817,699,900,000	1,233,039,000,000
2	456,885,400,000	579,131,400,000	838,180,900,000	1,196,460,000,000
3	457,218,300,000	577,178,500,000	863,445,000,000	1,298,005,000,000
4	455,247,600,000	576,113,500,000	852,695,900,000	1,223,217,000,000
5	463,297,000,000	583,980,900,000	851,854,800,000	1,182,330,000,000
6	454,917,900,000	566,498,300,000	827,387,000,000	1,289,460,000,000
7	454,917,800,000	566,498,400,000	827,385,000,000	1,289,470,000,000
8	453,148,100,000	574,658,200,000	849,235,100,000	1,300,046,000,000
9	448,695,500,000	583,183,000,000	897,890,900,000	1,252,295,000,000
10	460,404,200,000	571,850,300,000	861,595,200,000	1,268,049,000,000
11	454,652,900,000	581,832,100,000	864,881,700,000	1,265,913,000,000
12	461,623,900,000	583,982,500,000	860,790,900,000	1,258,116,000,000
13	448,156,500,000	559,806,600,000	828,439,900,000	1,196,555,000,000
14	460,808,200,000	588,466,900,000	888,943,000,000	1,306,452,000,000
15	459,016,200,000	572,772,500,000	830,472,100,000	1,230,277,000,000
16	455,392,200,000	577,377,900,000	836,299,600,000	1,093,545,000,000
17	454,177,100,000	569,476,600,000	874,125,100,000	1,293,850,000,000
18	458,080,100,000	579,067,000,000	881,403,600,000	1,314,847,000,000
19	454,741,200,000	572,032,400,000	863,793,300,000	1,217,348,000,000
20	457,634,000,000	576,165,900,000	856,425,000,000	1,338,990,000,000
21	455,846,000,000	577,484,100,000	858,081,400,000	1,196,940,000,000
22	452,044,600,000	577,790,500,000	857,750,200,000	1,276,521,000,000
23	450,160,100,000	583,348,000,000	867,370,800,000	1,332,212,000,000
24	453,038,200,000	574,331,300,000	856,368,100,000	1,238,351,000,000
25	448,989,600,000	576,016,700,000	860,552,000,000	1,196,690,000,000
26	451,921,800,000	569,477,600,000	848,386,400,000	1,189,080,000,000
27	452,937,200,000	588,229,000,000	888,495,500,000	1,271,483,000,000
28	452,922,100,000	576,371,200,000	831,724,000,000	1,284,120,000,000
29	459,644,700,000	588,929,800,000	870,433,900,000	1,415,604,000,000
30	458,224,800,000	587,883,200,000	875,302,600,000	1,303,712,000,000
Average	**455,324,223,333**	**577,076,050,000**	**856,246,960,000**	**1,258,432,566,667**

3.

Bayesian_withREC (changing base year)	<LDA Output Negative Binomial-LogNormal Distribution Combination>			
Simulation #	90.0%	95.0%	99.0%	99.9%
1	892,160,100,000	1,139,806,000,000	1,731,740,000,000	2,424,102,000,000
2	895,627,800,000	1,135,592,000,000	1,709,030,000,000	2,464,182,000,000
3	899,108,600,000	1,137,758,000,000	1,739,894,000,000	2,466,421,000,000
4	902,112,900,000	1,160,149,000,000	1,729,680,000,000	2,469,669,000,000
5	892,369,200,000	1,134,252,000,000	1,728,810,000,000	2,476,836,000,000
6	913,701,800,000	1,158,739,000,000	1,676,667,000,000	2,416,242,000,000
7	905,053,400,000	1,131,233,000,000	1,681,467,000,000	2,634,267,000,000
8	892,275,000,000	1,140,428,000,000	1,702,977,000,000	2,451,733,000,000
9	917,701,400,000	1,167,829,000,000	1,734,514,000,000	2,474,119,000,000
10	912,486,400,000	1,144,208,000,000	1,685,453,000,000	2,379,036,000,000
11	909,214,100,000	1,153,103,000,000	1,743,727,000,000	2,660,622,000,000
12	912,462,600,000	1,152,659,000,000	1,711,827,000,000	2,559,049,000,000
13	894,585,400,000	1,130,236,000,000	1,687,551,000,000	2,372,538,000,000
14	896,784,400,000	1,162,738,000,000	1,693,089,000,000	2,513,474,000,000
15	921,288,000,000	1,162,484,000,000	1,753,398,000,000	2,687,176,000,000
16	889,052,600,000	1,140,195,000,000	1,753,657,000,000	2,621,266,000,000
17	891,449,300,000	1,138,913,000,000	1,662,819,000,000	2,576,436,000,000
18	895,263,800,000	1,142,043,000,000	1,693,014,000,000	2,333,213,000,000
19	911,414,600,000	1,156,296,000,000	1,679,964,000,000	2,546,100,000,000
20	907,347,300,000	1,132,115,000,000	1,719,131,000,000	2,342,912,000,000
21	914,707,000,000	1,165,180,000,000	1,787,016,000,000	2,507,489,000,000
22	895,706,000,000	1,119,107,000,000	1,659,820,000,000	2,400,266,000,000
23	905,599,800,000	1,137,104,000,000	1,768,586,000,000	2,525,329,000,000
24	904,320,200,000	1,151,087,000,000	1,695,742,000,000	2,587,489,000,000
25	914,354,800,000	1,152,978,000,000	1,701,754,000,000	2,412,772,000,000
26	917,094,800,000	1,165,500,000,000	1,692,487,000,000	2,631,864,000,000
27	892,163,600,000	1,150,260,000,000	1,769,377,000,000	2,809,362,000,000
28	905,931,400,000	1,159,751,000,000	1,740,917,000,000	2,533,805,000,000
29	914,878,100,000	1,170,860,000,000	1,710,906,000,000	2,488,747,000,000
30	895,632,400,000	1,138,461,000,000	1,692,901,000,000	2,493,014,000,000
Average	**903,728,226,667**	**1,147,702,133,333**	**1,714,597,166,667**	**2,508,651,000,000**

4.

MLE_with REC (changing base year)	<LDA Output Negative Binomial-LogNormal Distribution Combination>			
Simulation #	90.0%	95.0%	99.0%	99.9%
1	1,015,805,000,000	1,310,568,000,000	1,920,442,000,000	2,646,369,000,000
2	1,021,654,000,000	1,299,302,000,000	1,918,601,000,000	2,796,686,000,000
3	1,029,493,000,000	1,305,474,000,000	1,879,334,000,000	2,734,125,000,000
4	1,016,535,000,000	1,287,724,000,000	1,979,781,000,000	2,705,159,000,000
5	1,021,436,000,000	1,302,154,000,000	1,883,976,000,000	2,576,318,000,000
6	1,024,878,000,000	1,310,958,000,000	1,916,397,000,000	2,688,913,000,000
7	1,027,069,000,000	1,301,206,000,000	1,964,044,000,000	2,747,414,000,000
8	1,046,383,000,000	1,334,178,000,000	1,927,146,000,000	2,745,689,000,000
9	1,015,757,000,000	1,303,785,000,000	1,998,034,000,000	2,892,573,000,000
10	1,018,917,000,000	1,290,753,000,000	1,886,660,000,000	2,777,946,000,000
11	1,025,979,000,000	1,294,638,000,000	1,934,682,000,000	2,830,085,000,000
12	1,039,754,000,000	1,308,173,000,000	1,964,844,000,000	2,713,751,000,000
13	1,038,598,000,000	1,327,821,000,000	1,952,118,000,000	2,892,548,000,000
14	1,034,059,000,000	1,317,806,000,000	1,992,832,000,000	2,865,099,000,000
15	1,011,855,000,000	1,283,266,000,000	1,857,354,000,000	2,596,680,000,000
16	1,025,373,000,000	1,278,516,000,000	1,840,166,000,000	2,791,999,000,000
17	1,040,507,000,000	1,318,127,000,000	1,977,074,000,000	2,866,438,000,000
18	1,039,759,000,000	1,328,353,000,000	1,875,424,000,000	2,650,404,000,000
19	1,035,895,000,000	1,298,416,000,000	1,914,311,000,000	2,927,566,000,000
20	1,037,455,000,000	1,283,980,000,000	1,932,483,000,000	2,921,423,000,000
21	1,018,780,000,000	1,292,664,000,000	1,934,992,000,000	2,907,697,000,000
22	1,035,025,000,000	1,324,143,000,000	1,989,722,000,000	2,750,083,000,000
23	1,026,189,000,000	1,286,846,000,000	1,866,400,000,000	2,827,296,000,000
24	1,015,905,000,000	1,298,808,000,000	1,955,883,000,000	2,728,099,000,000
25	1,027,403,000,000	1,296,729,000,000	1,977,388,000,000	2,730,504,000,000
26	1,032,952,000,000	1,312,357,000,000	1,878,028,000,000	2,802,566,000,000
27	1,028,463,000,000	1,295,121,000,000	1,950,871,000,000	2,633,323,000,000
28	1,027,331,000,000	1,296,017,000,000	1,871,639,000,000	2,816,496,000,000
29	1,029,777,000,000	1,309,535,000,000	1,932,033,000,000	2,915,689,000,000
30	1,032,760,000,000	1,292,468,000,000	1,885,435,000,000	2,807,272,000,000
Average	**1,028,058,200,000**	**1,302,996,200,000**	**1,925,269,800,000**	**2,776,207,000,000**

5.

Bayesian_withoutREC (fixed base year)	<LDA Output Negative Binomial-LogNormal Distribution Combination>			
Simulation #	90.0%	95.0%	99.0%	99.9%
1	862,718,900,000	1,101,525,000,000	1,644,869,000,000	2,484,832,000,000
2	878,542,400,000	1,120,792,000,000	1,615,155,000,000	2,403,720,000,000
3	867,239,900,000	1,102,472,000,000	1,670,151,000,000	2,510,249,000,000
4	883,802,400,000	1,120,217,000,000	1,641,746,000,000	2,402,009,000,000
5	870,814,800,000	1,119,973,000,000	1,666,926,000,000	2,372,890,000,000
6	878,304,300,000	1,097,157,000,000	1,739,616,000,000	2,415,999,000,000
7	864,160,100,000	1,107,158,000,000	1,719,329,000,000	2,587,594,000,000
8	880,583,300,000	1,135,518,000,000	1,667,303,000,000	2,395,678,000,000
9	880,254,400,000	1,139,170,000,000	1,687,446,000,000	2,458,023,000,000
10	886,290,600,000	1,109,034,000,000	1,646,339,000,000	2,489,400,000,000
11	874,342,300,000	1,136,270,000,000	1,693,566,000,000	2,456,073,000,000
12	870,646,700,000	1,113,327,000,000	1,614,266,000,000	2,311,856,000,000
13	874,352,200,000	1,118,937,000,000	1,713,783,000,000	2,345,431,000,000
14	870,436,800,000	1,106,464,000,000	1,678,814,000,000	2,507,458,000,000
15	868,515,700,000	1,105,820,000,000	1,673,554,000,000	2,475,845,000,000
16	861,937,100,000	1,105,750,000,000	1,720,087,000,000	2,461,213,000,000
17	881,121,300,000	881,121,300,000	1,675,706,000,000	2,291,291,000,000
18	883,576,800,000	1,118,585,000,000	1,630,973,000,000	2,431,077,000,000
19	871,211,000,000	1,101,008,000,000	1,637,847,000,000	2,285,566,000,000
20	873,344,700,000	1,111,824,000,000	1,720,652,000,000	2,455,942,000,000
21	874,714,100,000	1,107,344,000,000	1,630,185,000,000	2,647,223,000,000
22	845,721,000,000	1,095,284,000,000	1,659,464,000,000	2,634,518,000,000
23	859,441,500,000	1,112,088,000,000	1,634,669,000,000	2,436,373,000,000
24	873,424,400,000	1,115,472,000,000	1,691,959,000,000	2,608,244,000,000
25	862,748,200,000	1,099,897,000,000	1,586,097,000,000	2,439,478,000,000
26	882,044,900,000	1,096,046,000,000	1,579,606,000,000	2,379,962,000,000
27	871,485,300,000	1,107,368,000,000	1,585,006,000,000	2,198,167,000,000
28	874,718,000,000	1,133,427,000,000	1,653,299,000,000	2,552,237,000,000
29	861,170,700,000	1,111,561,000,000	1,684,428,000,000	2,582,279,000,000
30	870,537,200,000	1,116,241,000,000	1,622,274,000,000	2,484,987,000,000
Average	**843,812,935,484**	**1,069,253,235,484**	**1,605,971,451,613**	**2,371,148,838,710**

6.

MLE_without REC (fixed base year)	<LDA Output Negative Binomial-LogNormal Distribution Combination>			
Simulation #	90.0%	95.0%	99.0%	99.9%
1	1,071,921,000,000	1,351,994,000,000	1,910,687,000,000	2,740,792,000,000
2	1,076,495,000,000	1,339,025,000,000	1,932,385,000,000	2,694,228,000,000
3	1,085,592,000,000	1,366,202,000,000	1,954,317,000,000	2,878,864,000,000
4	1,087,060,000,000	1,356,180,000,000	1,930,074,000,000	2,834,981,000,000
5	1,078,863,000,000	1,346,135,000,000	1,977,663,000,000	2,674,109,000,000
6	1,090,927,000,000	1,363,636,000,000	1,942,191,000,000	2,630,377,000,000
7	1,080,317,000,000	1,345,115,000,000	1,982,470,000,000	2,811,315,000,000
8	1,079,406,000,000	1,361,874,000,000	1,982,664,000,000	2,818,077,000,000
9	1,059,676,000,000	1,321,777,000,000	1,923,579,000,000	2,666,819,000,000
10	1,093,221,000,000	1,367,293,000,000	1,972,457,000,000	2,848,444,000,000
11	1,073,998,000,000	1,343,803,000,000	1,990,749,000,000	2,849,954,000,000
12	1,073,998,000,000	1,343,803,000,000	1,990,749,000,000	2,849,954,000,000
13	1,081,856,000,000	1,351,308,000,000	1,971,706,000,000	2,760,993,000,000
14	1,084,627,000,000	1,354,503,000,000	1,992,007,000,000	3,000,270,000,000
15	1,085,293,000,000	1,364,971,000,000	1,951,207,000,000	2,734,827,000,000
16	1,075,718,000,000	1,350,937,000,000	1,955,583,000,000	2,754,100,000,000
17	1,049,092,000,000	1,308,715,000,000	1,925,071,000,000	2,746,580,000,000
18	1,057,785,000,000	1,316,355,000,000	1,918,603,000,000	2,554,544,000,000
19	1,066,168,000,000	1,321,284,000,000	1,904,903,000,000	2,747,226,000,000
20	1,076,392,000,000	1,329,130,000,000	1,916,072,000,000	2,794,097,000,000
21	1,079,137,000,000	1,340,289,000,000	1,954,436,000,000	2,784,473,000,000
22	1,069,328,000,000	1,351,332,000,000	1,957,030,000,000	2,905,623,000,000
23	1,077,041,000,000	1,375,637,000,000	2,002,218,000,000	2,955,174,000,000
24	1,078,648,000,000	1,345,566,000,000	1,935,266,000,000	2,703,357,000,000
25	1,076,231,000,000	1,351,137,000,000	1,923,803,000,000	2,489,153,000,000
26	1,079,299,000,000	1,349,433,000,000	1,985,149,000,000	2,831,786,000,000
27	1,062,132,000,000	1,337,850,000,000	1,937,802,000,000	2,705,820,000,000
28	1,077,257,000,000	1,347,889,000,000	1,957,313,000,000	2,955,993,000,000
29	1,068,127,000,000	1,356,975,000,000	2,036,418,000,000	2,901,691,000,000
30	1,098,114,000,000	1,365,166,000,000	1,981,172,000,000	2,587,987,000,000
Average	**1,041,732,870,968**	**1,304,042,387,097**	**1,893,411,096,774**	**2,684,245,419,355**

7.

Bayesian_withREC (fixed base year)	<LDA Output Negative Binomial-LogNormal Distribution Combination>			
Simulation #	90.0%	95.0%	99.0%	99.9%
1	2,234,693,000,000	2,810,331,000,000	4,078,603,000,000	5,713,743,000,000
2	2,205,831,000,000	2,782,260,000,000	3,905,620,000,000	5,589,168,000,000
3	2,205,298,000,000	2,739,159,000,000	3,839,300,000,000	5,608,070,000,000
4	2,166,563,000,000	2,683,094,000,000	3,884,543,000,000	5,362,901,000,000
5	2,176,151,000,000	2,727,848,000,000	4,165,194,000,000	5,965,073,000,000
6	2,187,873,000,000	2,728,890,000,000	3,965,664,000,000	5,531,733,000,000
7	2,224,715,000,000	2,731,807,000,000	3,905,523,000,000	5,310,366,000,000
8	2,192,554,000,000	2,774,679,000,000	4,037,430,000,000	5,762,889,000,000
9	2,195,854,000,000	2,743,971,000,000	3,843,159,000,000	5,421,823,000,000
10	2,169,762,000,000	2,777,922,000,000	3,918,586,000,000	5,644,147,000,000
11	2,168,496,000,000	2,702,653,000,000	3,990,941,000,000	5,993,971,000,000
12	2,226,202,000,000	2,747,431,000,000	3,924,896,000,000	5,558,552,000,000
13	2,201,260,000,000	2,736,781,000,000	3,945,073,000,000	6,042,695,000,000
14	2,199,541,000,000	2,733,336,000,000	3,999,656,000,000	5,711,843,000,000
15	2,189,070,000,000	2,703,700,000,000	3,882,490,000,000	5,336,874,000,000
16	2,194,341,000,000	2,745,481,000,000	4,011,455,000,000	5,817,789,000,000
17	2,183,399,000,000	2,729,804,000,000	3,999,963,000,000	5,481,330,000,000
18	2,226,384,000,000	2,737,707,000,000	3,928,214,000,000	5,649,571,000,000
19	2,205,950,000,000	2,720,558,000,000	3,933,119,000,000	5,386,977,000,000
20	2,181,305,000,000	2,723,881,000,000	3,887,135,000,000	5,631,576,000,000
21	2,170,993,000,000	2,679,184,000,000	3,933,440,000,000	5,704,376,000,000
22	2,198,577,000,000	2,727,051,000,000	3,884,038,000,000	5,484,455,000,000
23	2,164,419,000,000	2,693,473,000,000	3,797,850,000,000	5,496,677,000,000
24	2,170,861,000,000	2,667,003,000,000	3,941,035,000,000	5,777,670,000,000
25	2,154,484,000,000	2,678,083,000,000	3,919,804,000,000	5,414,480,000,000
26	2,182,326,000,000	2,719,835,000,000	3,983,866,000,000	5,694,758,000,000
27	2,203,935,000,000	2,755,558,000,000	3,927,882,000,000	5,638,129,000,000
28	2,204,550,000,000	2,734,295,000,000	3,899,873,000,000	5,669,605,000,000
29	2,205,297,000,000	2,718,472,000,000	3,952,960,000,000	5,543,432,000,000
30	2,187,517,000,000	2,757,630,000,000	3,982,429,000,000	5,598,828,000,000
Average	**2,192,606,700,000**	**2,730,395,900,000**	**3,942,324,700,000**	**5,618,116,700,000**

8.

MLE_with REC (fixed base year)	<LDA Output Negative Binomial-LogNormal Distribution Combination>			
Simulation #	90.0%	95.0%	99.0%	99.9%
1	2,447,083,000,000	3,069,049,000,000	4,465,893,000,000	6,156,911,000,000
2	2,412,627,000,000	3,017,639,000,000	4,366,945,000,000	6,392,436,000,000
3	2,379,265,000,000	3,033,894,000,000	4,316,407,000,000	6,411,102,000,000
4	2,468,173,000,000	3,076,984,000,000	4,388,884,000,000	6,225,112,000,000
5	2,427,000,000,000	2,999,680,000,000	4,358,003,000,000	6,192,061,000,000
6	2,415,994,000,000	3,038,983,000,000	4,484,160,000,000	6,359,370,000,000
7	2,466,274,000,000	3,131,308,000,000	4,433,377,000,000	6,418,972,000,000
8	2,429,111,000,000	3,035,116,000,000	4,322,067,000,000	5,986,208,000,000
9	2,482,492,000,000	3,102,454,000,000	4,468,628,000,000	5,762,744,000,000
10	2,534,562,000,000	3,156,983,000,000	4,551,813,000,000	6,090,296,000,000
11	2,478,298,000,000	3,072,562,000,000	4,397,371,000,000	6,391,474,000,000
12	2,493,065,000,000	3,125,531,000,000	4,529,110,000,000	6,369,604,000,000
13	2,446,418,000,000	3,099,943,000,000	4,442,854,000,000	6,418,268,000,000
14	2,452,450,000,000	3,029,794,000,000	4,337,532,000,000	6,164,927,000,000
15	2,403,566,000,000	3,042,779,000,000	4,350,408,000,000	6,634,613,000,000
16	2,482,042,000,000	3,147,799,000,000	4,618,030,000,000	6,259,761,000,000
17	2,444,509,000,000	3,063,980,000,000	4,503,559,000,000	6,394,034,000,000
18	2,474,425,000,000	3,104,984,000,000	4,571,374,000,000	6,545,961,000,000
19	2,427,841,000,000	3,096,861,000,000	4,410,145,000,000	6,620,265,000,000
20	2,462,969,000,000	3,104,986,000,000	4,421,982,000,000	6,402,110,000,000
21	2,431,090,000,000	3,042,824,000,000	4,365,400,000,000	6,287,646,000,000
22	2,430,962,000,000	3,043,362,000,000	4,534,889,000,000	6,425,777,000,000
23	2,467,788,000,000	3,093,560,000,000	4,379,853,000,000	6,099,118,000,000
24	2,452,297,000,000	3,056,743,000,000	4,398,451,000,000	6,220,558,000,000
25	2,462,736,000,000	3,073,831,000,000	4,375,251,000,000	6,423,302,000,000
26	2,439,353,000,000	3,044,473,000,000	4,519,497,000,000	6,349,352,000,000
27	2,451,405,000,000	3,051,067,000,000	4,363,244,000,000	6,146,176,000,000
28	2,503,058,000,000	3,138,443,000,000	4,592,295,000,000	6,334,183,000,000
29	2,454,476,000,000	2,973,470,000,000	4,406,495,000,000	6,176,280,000,000
30	2,458,817,000,000	3,082,052,000,000	4,565,584,000,000	6,428,161,000,000
Average	**2,452,671,533,333**	**3,071,704,466,667**	**4,441,316,700,000**	**6,302,892,733,333**

Abstract

Solar Developers' Losses due to Sunshine Duration Shortfall and Marketability of Sunshine Insurance: A Loss Distribution Approach

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Photovoiltaic energy is a rapidly increasing renewable energy source in Korea. As of 2014, it constituted 4.7% of the renewable energy mix, an increase of 58.9% from the previous year (KEA, 2014). To maintain this trend, it is essential to minimize solar generation volatility and other risks related to solar energy development. Solar developers face market risks (SMP and REC price, FIT and PPA availability, etc.), technical risk (system performance, tests reliability, infrastructure level, etc.), weather/climate risk (extreme weather events, natural disasters, solar radiation/sunshine shortfall, etc.). Among those, this paper will focus on sunshine duration shortfall, since it is one of the factors that systematically affects solar energy developers and has high correlation with the amount of solar energy produced (as much as 0.8 according to some empirical studies in South Korea). This paper will analyze the typical risk mitigation tool, insurance against potential losses, which can be categorized as business interruption insurance.

Despite of the high correlation between generated energy output and sunshine duration hours, only

a few Korean insurance companies offer solar insurance, and with little success so far. To examine the potential demand, this paper will first compute the number of cities that have faced sunshine shortfall on yearly basis from 1990 to 2015. This paper created two plausible criteria defining sunshine shortfall: 1) when an average annual sunshine duration hour in a particular city and year falls more than 10% of the historical average (scenario 1) or when the same variable drops over 20% of the historical average (scenario 2). The former scenario will be discussed in detail, whereas the latter scenario will be used for suggestion part of this paper. Based on the frequency of sunshine shortfall events and solar developers′ revenue estimation, this paper will calculate the severity of the losses due to sunshine shortfall.

Based on this information, the paper will derive the most suitable probability distribution describing the frequency and severity of the events, respectively. Then, it will check for their statistical significance by using Kolmogorov-Smirnov and Anderson-Darling tests. After selecting the distributions that match the data, this paper will estimate the parameters for each case using Maximum Likelihood Estimation and Bayesian Estimation methods. The two methods will be applied separately on the same data set in order to improve the credibility of the results and provide richer information on the topic. Then, for each combination set of the estimated parameters, this paper will apply Loss Distribution Approach (LDA), the method often used in the evaluation of operational risk, by summing yearly risk and conjugating the frequency and severity distributions to obtain 50th, 75th, 90th, 99th and 99.9th percentile of the aggregate loss distribution. Finally, this paper will perform a simulation on the LDA results 30 times for each paired outcome of frequency and severity to use the average value of each set for risk interpretation.

This paper intends to assess the attractiveness of sunshine shortfall insurance both from the perspective of solar developers and insurance companies. By calculating different percentiles of Value at Risk with the use of Loss Distribution approach, this paper will try to answer why sunshine (or solar radiation) shortfall insurance is still an infantile industry and why the current providers have to offer it at high premiums. This paper is the first academic research in Korea that answers 1) how

much volatility sunshine duration has; 2) based on the synthesis of current sunshine shortfall contracts, what the following revenue loss due to sunshine shortfall is; 3) how the result change if we considered more realistic (by incorporating Renewable Energy Certificates sales revenues inside) calculations of sunshine shortfall; 4) whether climate change affects average yearly sunshine duration hours and how it can be translated into a higher risk for insurance companies; 5) whether it is possible to make sunshine duration insurance affordable to more solar developers.

There are four important findings in this paper. First, risk value exceeds insured value at high percentiles. Consequently, it is reasonable to assess the realizable risk at 50th and 75th percentiles of the aggregate probability distribution. Second, when rescaled at per KW level, fixing the base year at 1990th level creates risk value 2.2 to 2.6 times higher than with moving base year (based on the sunshine duration average of directly preceding 10 years). Third, by incorporating RECs in solar developers' risk valuation, this paper concludes that the risk will soar by 1.9 to 2.3 times. Finally, although this paper focused on scenario 1, which defined sunshine duration shortfall as any shortfall below 10% of the historic average, it also suggested an alternative, where sunshine shortfall is defined as any shortfall below 20% of historic average. The results showed that an insurance product following the latter insurance structure could reduce the premium much more than in the former insurance structure. In the less riskier insurance structure case, the ratio of fixed costs to insurance premiums and the share of insurance premiums in energy sales revenue were close to the NREL(2010) indicators, making it more realizable.

◆ Keywords : Loss Distribution Approach, Monte Carlo Simulation, Bayesian Statistics, Maximum Likelihood Estimation, Solar Insurance, Climate Change

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