Application of Numerical Methods to Optimize the Global Photovoltaic Supply Chain

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1. INTRODUCTION

Due to the improvement of efficiency and the reduction in its cost, photovoltaic (PV) is one of expected options of renewable energies in the future. If the conventional power plants are replaced by PVs, the primary energy consumption at their power plants could be reduced and the CO2 emission from them could be reduced as well. On the other hand, it is usually pointed out that the CO2 emission comes from its manufacturing stages. Therefore, it is important to investigate its CO2 emissions from life cycle perspective [1].

However, the CO2 emission from each stage strongly depends on its location. The CO2 emissions to manufacture PV and its materials are determined by the CO2 emission per electricity in their power grid. Also, the reduction in the CO2 emission at the usage stage is determined by its weather conditions and the CO2 emission per electricity at the location. Those values could be changed drastically for each location and country. Therefore, it could be effective to optimize the allocations of their stages in its supply chain to reduce the ir life cycle CO2 emission.

In our previous study, the PV potential in the world is clarified [2]. And also, basing on the analytical framework, we clarify the life cycle CO2 emission of PV for different combinations of countries in its supply chain [3]. In that study, we manually obtain the combination of countries from just top 5 countries for seven stages. However, it is not efficient to investigate the best combination manually when the numbers of countries and stages increase because the number of possible combinations becomes too large.

The objective of this study is to investigate the usability of some numerical methods to optimize such a large and complex supply chain using the case study of PV industry Dijkstra algorithm, which is one kind of dynamic programming methods to optimize the network system, and Monte Carlo simulation are applied to optimize the global supply chain of PV. Finally, we clarify how much CO2 emission can be reduced at most in the present supply chain. These analytical frameworks could be generally applicable to another decision making situations with path dependency, large number of options, and many stages such as the complex manufacturing processes.

2. METHOD

2.1. Functional unit and system boundary

Here, we assume a functional unit of 1kW multi-crystalline silicon PV system with 20 years life time. The system boundary is structured by the following seven stages such as production of solar grade silicon (SOG-Si) at Stage 1, production of poly silicon (Si) at Stage 2, production of Si ingot at Stage 3, production of Si wafer at Stage 4, production of cell at Stage 5, production of module at Stage 6, and usage and waste at Stage 7. While CO2 emission to manufacture a balance of system (BOS) is also considered, the value is assumed to be constant. The CO2 emission of shipment is also considered. The recycle of PV is neglected.

2.2. Numerical methods

Figure 1 shows the example of supply chain modeling. In this figure, A, B, C, and D mean the countries which can be options at each stage. For example, while the A can be in every stage, the B cannot be in Stage 3. The linkage between the nodes shows the options toward the next stage. For example, if the supply chain starts from A at Stage 1, there are two options to go to Stage 4 as A→A→D→D with total 45 CO2 emission or A→D→D→D with total 60 CO2 emission. This model is path dependent model. Therefore, linear optimization method cannot be applied directly.

For each stage, while there are a number of possible locations around the world, we limited to the number of countries for each stage to 5, 19, 14, 21, 32, 44, and 21 for the stages from Stage 1 to Stage 7 in the present supply chain, respectively basing on the actual statistical data [4-5].

In Monte Carlo method, the probability to select the country at each stage is determined by their market shares in 2009 [4]. The number of iterations of Monte Carlo method is 10000 times.
3. RESULTS AND DISCUSSIONS

The number of combinations is more than $8.3 \times 10^8$ in this study. The optimum supply chain is successfully obtained within short time by the Dijkstra algorithm. The maximum CO$_2$ reduction is 29 tons for the best combination of the countries such as Canada, Norway, Norway, Norway, Switzerland, and Australia from Stage 1 to Stage 7, respectively. In this case, the CO$_2$ payback time is nearly half year.

Figure 2 shows the possibility distribution by Monte Carlo method for the PV supply chain basing on the data in 2009. As shown in this figure, the largest possibility is on 6 tons CO$_2$ reduction. The maximum CO$_2$ reduction is 28 tons. This value is close to that obtained by Dijkstra method. In the worst cases, in which PV is installed into Switzerland or France, the total CO$_2$ emission increases. This is because their CO$_2$ emissions per electricity are very small and consequently the amount of CO$_2$ reduction at the usage stages is smaller than that at the manufacturing stages.

Figure 3 shows the possibility distribution of total CO$_2$ emission in 2009.

4. CONCLUSIONS

In this study, we demonstrated some numerical techniques to investigate the optimum supply chain of photovoltaic industry. Network modeling is very useful to find out the optimum path to minimize CO$_2$ emission in the world. The CO$_2$ emission for the optimum supply chain is 29 tons during the PV’s life cycle.

On the other hand, Monte Carlo simulation is useful to know the variation of CO$_2$ emissions and also the possibility of them. In this study, the range of total CO$_2$ emission is from -28 ton to 1 tons and the mean is on -6 tons. It is clarified that CO$_2$ emission could increase for the worst supply chain.

These numerical methods have its specific advantages. Then, users should use the suitable methods depending on its objectives.

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