

Article

# Uncertainty Simulation of Wood Chipping Operation for Bioenergy Based on Queuing Theory

Mika Yoshida \*  and Katsuhiko Takata

Institute of Wood Technology, Akita Prefectural University. Kaiezaka 11-1, Noshiro, Akita 016-0876, Japan; katsu@iwt.akita-pu.ac.jp

\* Correspondence: mika@iwt.akita-pu.ac.jp; Tel.: +81-185-526-900

Received: 19 August 2019; Accepted: 13 September 2019; Published: 19 September 2019



**Abstract:** Managing uncertainty is the way to secure stability of the supply chain. Uncertainty within chipping operation and chip transportation causes production loss. In the wood chip supply chain for bioenergy, operational uncertainty mainly appears in the moisture content of the material, chipping productivity, and the interval of truck arrival. This study theoretically quantified the loss in wood chip production by applying queuing theory and stochastic modelling. As well as the loss in production, the inefficiency was identified as the idling time of chipper and the queuing time of trucks. The aim of this study is to quantify the influence of three uncertainties on wood chip production. This study simulated the daily chip production using a mobile chipper by applying queuing theory and stochastic modelling of three uncertainties. The result was compared with the result of deterministic simulation which did not consider uncertainty. Uncertainty reduced the production by 14% to 27% compared to the production of deterministic simulation. There were trucks scheduled but not used. The cases using small trucks show the largest daily production amount, but their lead time was the longest. The large truck was sensitive to the moisture content of material because of the balance between payload and volumetric capacity. This simulation method can present a possible loss in production amount and enables to evaluate some ways for the loss compensation quantitatively such as outsourcing or storing buffer. For further development, the data about the interval of truck arrival should be collected from fields and analyzed. We must include the other uncertainties causing technical and operator delays.

**Keywords:** interval of truck arrival; lead time; logistics; moisture content; stochastic modelling; throughput; work in process

## 1. Introduction

Woody biomass has been used for heat generation for a long time, and also for power generation for the last several decades as one of the renewable energy resources. Globally, as represented by the movement of bioeconomy in European countries, it is promoted to develop end products with higher added value from woody biomass by advanced processing/refining technologies in material/energy use. This type of shift in end products requires the expansion of scale and inadequate design of the supply chain may not be economically, environmentally, and socially sustainable [1].

In Japan, woody biomass is featured by the use for power generation as the replacement of fossil fuel in the context of bioeconomy. It is a relatively new idea compared to traditional material use and has been promoted since 2012 by Feed-In Tariff law [2]. The Japanese government targets to reduce the green house gas emission by 26% till 2030 compared to that in 2013 according to Paris Agreement [3]. To achieve this target, the production of forest resources is expected to be increased for both material and energy uses [3] so that it is evident that the shift in end products by advanced technologies will also be a matter of time in Japan. The existing supply chain of woody biomass has to be modified to

conquer the difficulties which induce a high cost of supply chain management [4] not only for local energy supply but also for the future society.

Energy is the final usage of woody biomass. The low-quality part, such as residues, treetops, and timbers with defects, can get market value while it has been abandoned previously. The price of wood for energy is generally the lowest among the wood product so that the design of the supply chain must be optimal. The key cost component is transportation in the woody biomass supply chain [1]. Network-based modelling helps to build an optimally designed supply chain [4]. Several optimization methods in linear programming and heuristics are utilized to support decision making on harvesting planning such as harvesting location and system selection in practice in combination with geographic information [5,6]. The outcome of optimization shows the best or a near-optimal solution to minimize the transportation cost deterministically while maintaining stable supply [7]. Such an optimized solution is determined under a particular situation without uncertainty. Uncertainty within a supply chain should be considered because it leads to the infeasibility or sub-optimality of the supply chain which is optimized [7–9].

In a woody biomass supply chain, uncertainty exists in biomass procurement, demand, price, geographical/environmental condition, and other unforeseen events. From the aspect of stability and economy, a supply system using mobile chippers at landings in a forest which is widely used for producing chip from low-quality wood [10,11] needs an empty truck to discharge the produced wood chip. Such interactive characteristic is called “hot system” [12]. This interaction between chipping and transportation causes delays and brings the loss in the production which jeopardized the stable supply of woody biomass [13]. Three major factors act as uncertainty in mobile chipping operation which affects the production amount.

Firstly, the piece size of raw material affected chipping productivity [14] and a stochastic simulation had shown the influence caused by the interaction with loading operation [15]. Secondary, the moisture content of raw material influence on the volume of material which could be loaded on a truck [16,17]. Natural drying of raw material proceeded unevenly to make the variance in the moisture content after drying [18]. Thirdly, the scheduling of transportation related to the idling time of the mobile chipper [19] which can be simulated by queuing theory.

Queuing theory is a traditional operational research method which is used for simulating uncertainty in hot systems. Uncertainty in operations can be illustrated stochastically [7], and queuing theory and stochastic modelling of uncertainty are applicable to estimate the loss of production due to the idling of mobile chipper and the extension of lead time due to queuing time of a truck [20]. While these delays are not included in productivity evaluation usually, the value of throughput can reflect the idling time of a chipper and queuing time of a truck in productivity evaluation in the effort to increase the production amount [20].

There are a few previous studies that dealt with a stochastic simulation of chipping and trucking interaction inspecting the influence of uncertainty in transportation distance and loading operations [12,21,22]. This study simulates the daily chip production using a mobile chipper based on queuing theory and stochastic modelling. The aim of this study is to quantify the influence of three uncertainties on the wood chip production theoretically to accelerate future studies and to contribute to thinking about the practical management of uncertainty.

## 2. Materials and Methods

This study simulated a mobile chipping operation. The cycle time of  $i$ -times of chipping operation  $ct_i$  (h oven-dry  $t^{-1}$ ) was expressed by Equation (1):

$$ct_i = t_{pr,i} + t_{idle,i} \quad (1)$$

where  $t_{pr,i}$  was the chip production time (h oven-dry  $t^{-1}$ ); and  $t_{idle,i}$  was the idling time of the chipper to wait for an empty truck coming (h oven-dry  $t^{-1}$ ).

### 2.1. Chip Production Time

The chip production time  $t_{pr,i}$  was defined by Equation (2):

$$t_{pr,i} = V_i / (d_{odt} p_{chip,i} / 1000), \tag{2}$$

where  $V_i$  was the loaded weight of a truck (oven-dry t);  $d_{odt}$ , the density of chip in oven-dry weight which was constant at 201 (oven-dry kg loose m<sup>-3</sup>) [23]; and  $p_{chip,i}$  was chipping productivity (loose m<sup>3</sup> h<sup>-1</sup>). The chip production time was assumed to be influenced by two uncertainties: chipping productivity and moisture content of material.

A truck-mounted chipper, MUS-MAX WT8-XL manufactured in Austria, was applied in this study because of its mobility and productivity [24]. Chipping productivity of this mobile chipper followed a normal distribution with the average,  $\mu = 66.37$ , and the variation,  $\sigma^2 = 7.79$  [15].

Moisture content (MC) defines the loaded volume due to the payload. MC is not evenly reduced [18]. According to the previous study [18], three ways of drying are assumed as shown in Table 1. Conventionally, there was no drying period, and the average MC was assumed to concentrate at 54 wet-based % (WB%). In Japan, the average MC of 33 WB% was achievable by natural drying for about 3 months, and the demand side recommended to reduce MC to this level. In this recommended case, there was a wide variance in moisture content because of the short drying period. After 273 days of drying, MC converged to around 16 WB% with a narrow variance. This drying type was assumed as the advanced type in this study. The loaded weight  $V_i$  was calculated by Equations (3) and (4) according to MC  $mc_i$ , the volumetric capacity of truck  $V_{volume}$  (loose m<sup>3</sup>), and the payload  $V_{weight}$  (t):

$$V_i = (1 - mc_i) V_{weight} \left( \frac{d_{odt} V_{volume}}{1 - mc_i} \geq V_{weight} \right), \tag{3}$$

$$V_i = d_{odt} V_{volume} \left( \frac{d_{odt} V_{volume}}{1 - mc_i} < V_{weight} \right). \tag{4}$$

**Table 1.** Drying types assumed in this study.

Type	Symbol	Definition	Explanation
Conventional	$MC_c$	$mc_i = 54$	No drying. The average MC is 54 WB% and no variance.
Recommended	$MC_r$	$mc_i \sim Normal[30, 10^2]$	Three-months drying. The average MC varied and assumed to follow the normal distribution with wider variance (mean = 30, SD = 10)
Advanced	$MC_a$	$mc_i \sim Normal[16, 2.56^2]$	One-year drying. The average MC slightly varied. By setting the coefficient of variation at the half of that in Recommended type, it assumed to follow the normal distribution (mean = 16, SD = 2.56)

These drying types were assumed based on Watanabe et al. (2017).

When the weight of full load exceeded the payload, the moisture content affected the loaded volume as Equation (3). When the weight did not exceed the payload, the space of the container could be fully used as Equation (4).

### 2.2. Idling Time of the Chipper and Queuing Time of a Truck

The idling time of the chipper to wait for an empty truck coming  $t_{idle,i}$  was calculated by Equation (5):

$$t_{idle,i} = \sum_{n=1}^i t_{arr,n} - \sum_{n=1}^{i-1} ct_n \left( t_{idle,i} \geq 0, i \geq 2 \right), \tag{5}$$

where  $t_{arr,i}$  was the interval of a truck arrival at the  $i$  cycle of operation (h); and  $t_{idle,1}$  equalled to  $t_{arr,1}$ . When the idling time of the chipper was a minus value at the cycle  $i$ , there was no idling time ( $t_{idle,i} = 0$ ) when the queuing time of a truck  $t_{que,i+1}$  occurred as Equation (6):

$$t_{que,i+1} = -t_{idle,i} \quad (t_{idle,i} < 0, t_{que,1} = 0). \tag{6}$$

The truck was scheduled based on its volume capacity assuming the situation where information of drying is unknown in advance. Assuming a Poisson process in truck arrival, the interval of a truck arrival follows an exponential distribution with the scheduled number of truck arrival  $\lambda$  during an hour (trucks  $h^{-1}$ ) to keep chipper working as Equations (7) and (8):

$$t_{arr,i} \sim Exp[\lambda], \tag{7}$$

$$\lambda = P_{chip} / V_{volume}. \tag{8}$$

The use of two sizes of trucks were assumed. The smaller truck was with  $20 \text{ m}^3$  of volume capacity and 9 tons of weight limit, and the larger truck was with  $40 \text{ m}^3$  of volume capacity and 11 tons of weight limit. The scheduled number of truck arrival  $\lambda$  was  $3.32 \text{ trucks } h^{-1}$  for smaller trucks and it was  $1.65 \text{ trucks } h^{-1}$  for larger trucks.

### 2.3. Evaluation

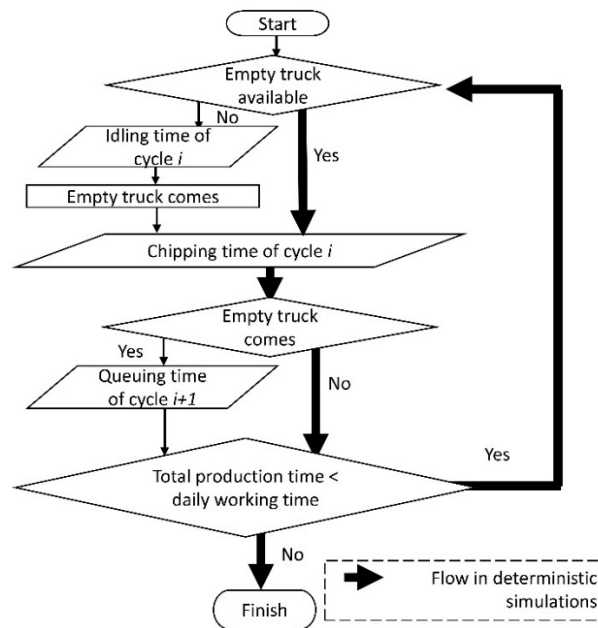
There are six stochastic cases according to truck sizes and drying types as shown in Table 2. This study simulated the daily operation for 10,000 times in each stochastic case as shown in Figure 1 and one daily working time  $H$  was 8 h. As control experiments, deterministic simulations were conducted for each simulation case. The difference between stochastic and deterministic simulations is also summarized in Table 3.

**Table 2.** Summary of simulation cases.

Case	Truck Size	Drying Type	Definition
S-C	Small	Conventional	No drying. Material was chipped and transported by small trucks.
S-R	Small	Recommended	After three-months drying, material was chipped and transported by small trucks.
S-A	Small	Advanced	After one-year drying, material was chipped and transported by small trucks.
L-C	Large	Conventional	No drying. Material was chipped and transported by large trucks.
L-R	Large	Recommended	After three-months drying, material was chipped and transported by large trucks.
L-A	Large	Advanced	After one-year drying, material was chipped and transported by large trucks.

**Table 3.** Difference between the stochastic and deterministic simulations.

Value	Symbol	Stochastic Simulation	Deterministic Model
Time of chipping operation at cycle $i$	$ct_i$	$= t_{pr,i} + t_{idle,i}$	$= t_{pr,i}$
Chipping productivity	$p_{chip,i}$	$\sim \text{Normal}[66.37, 7.79]$	$= 66.37$
Interval of a truck arrival	$t_{arr,i}$	$\sim \text{Exp}[\lambda]$	$= \frac{1}{\lambda}$
Moisture content	$mc_i$	$\left\{ \begin{array}{l} = 0.54 \\ \sim \text{Normal}[30, 10^2]/100 \\ \sim \text{Normal}[16, 2.56^2]/100 \end{array} \right.$	$\left\{ \begin{array}{l} = 0.54 \\ = 0.3 \\ = 0.16 \end{array} \right.$



**Figure 1.** Flowchart of a daily chipping simulation. The flow in bold arrow is the flow in deterministic simulation which does not occur idling and queuing times.

The following values were obtained for the evaluation of uncertainty: the total of productive working time of a chipper  $\sum t_{pr,i}$  (h); the number of trucks  $max(i)$  (trucks); the total amount of daily production  $\sum V_i$  (oven-dry t); the queuing time of a truck  $t_{que,i}$  (h truck<sup>-1</sup>); and the idling time of chipper  $t_{idle,i}$  (h). This study also introduced the idea of throughput (*TH*), lead time (*LT*), and work in process (*WIP*) that have a relationship as Equations (9)–(12) [20]:

$$TH = WIP / LT, \quad (9)$$

$$TH = \sum V_i / (\sum ct_i - t_{idle,1}), \quad (10)$$

$$LT = \sum (t_{pr,i} + t_{que,i}) / \sum V_i, \quad (11)$$

$$WIP = \sum (t_{pr,i} + t_{que,i}) / (\sum ct_i - t_{idle,1}). \quad (12)$$

The throughput indicates the hourly amount of production of a hot system (oven-dry t h<sup>-1</sup>). The throughput is the performance of the entire of a system and reflects the influence of uncertainty because it includes idling time, which are usually eliminated as organizational delays. It enables to evaluate systems in different conditions what makes a difference in uncertainty from two aspects, the work in process and the lead time. The lead time is the sum of the queuing time and the chip production time (h). The work in process is the amount in both the production process and the queue (oven-dry t). The simulation model was programmed, summarized, and visualized by using R-language [25].

### 3. Results

The results are summarized in Table 4. The amount of production was less by about 10–30 tons (14% to 27% of the performance) by uncertainties. In stochastic simulations, the productive working time of chipper ranged from 4.4 to 6.1 h. The gap in the number of trucks in stochastic and deterministic models told that there were several trucks scheduled but not used. The use of large trucks reduced the number of trucks which was necessary to run the daily production. The size of trucks defined the sensitivity to moisture content. In the cases S-C, S-R, and S-A, which used smaller trucks, the values were not influenced by the moisture content. In contrast, the cases L-C, L-R, and L-A, which used

larger trucks, showed that the productivity was improved as the moisture content reduced but the queuing time were getting worse.

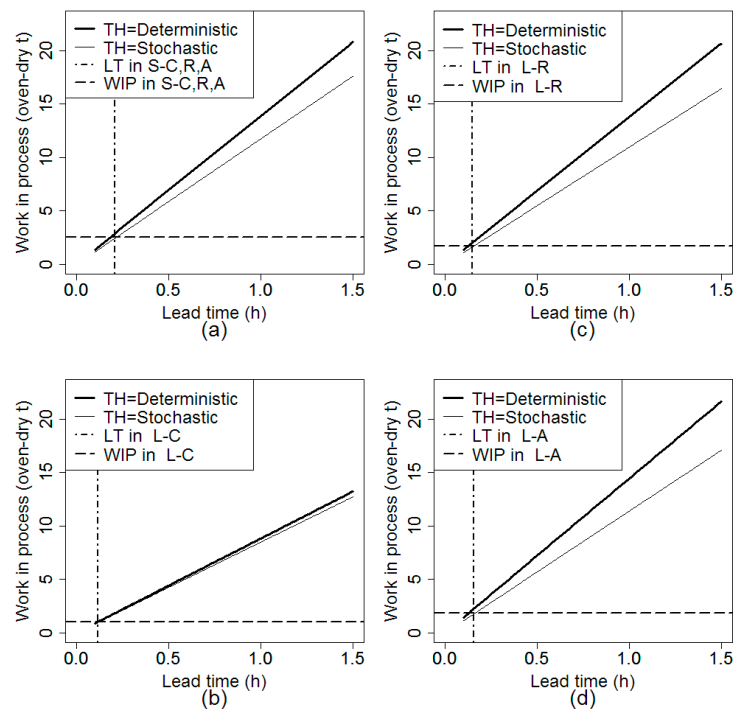
**Table 4.** Summary of the productive working time, number of trucks, the total amount of daily production, throughput, and the queuing and idling times.

Case		S-C	S-R	S-A	L-C	L-R	L-A
Productive working time of a chipper (h)	Average	6.06	6.04	6.07	4.36	5.59	5.81
	SD	0.8	0.81	0.8	1.11	1.13	1.1
	Deterministic	8	8	8	8	8	8
Number of trucks (trucks)	Average	20.06	20.02	20.11	11.48	10.04	9.63
	SD	2.66	2.67	2.65	2.91	2.04	1.81
	Deterministic	26.55	26.55	26.55	13.27	13.27	13.27
Total amount of daily production (oven-dry t)	Average	80.64	80.43	80.83	58.07	74.41	77.39
	SD	10.68	10.73	10.66	14.71	15.1	14.59
	Deterministic	106.72	106.72	106.72	67.16	102.2	106.72
Throughput (oven-dry t h <sup>-1</sup> )	Average	11.73	11.7	11.74	8.48	10.97	11.39
	SD	1.5	1.5	1.5	2.16	2.1	1.97
	Deterministic	13.86	13.86	13.86	9.08	13.82	14.43
Queuing time (h truck <sup>-1</sup> )	Average	0.54	0.53	0.55	0.2	0.54	0.63
	SD	0.35	0.35	0.35	0.18	0.41	0.46
	Deterministic	0	0	0	0	0	0
Idling time (h)	Average	1.13	1.15	1.12	3.13	1.82	1.6
	SD	0.83	0.84	0.83	1.27	1.25	1.19
	Deterministic	0	0	0	0	0	0

The lead time of the deterministic simulation was 0.075 h. We observed an extension of lead time by the queuing time of a truck. The lead time was 0.21 h on average (SD = 0.09) in the cases S-R, S-R, and S-A. That was 0.12 h (SD = 0.04) in the case L-C, and 0.15 h (SD = 0.06) in the cases L-R and L-A, respectively.

The throughput and its relationship with the work in process and the lead time are shown in Figure 2. The cases using small trucks (S-C, S-R, and S-A) achieved the best throughput followed by the cases L-C, L-R, and L-A. In the cases using small trucks, the values of throughput, work in process, and lead time were the same (Figure 2a). In the case L-C, the throughput was much less than the other cases, but the difference between the deterministic and stochastic simulations was the least (Figure 2b). In the cases L-R and L-A, the throughputs were similar to each other in both deterministic and stochastic basis (Figure 2c,d). Those values are also similar to the values in the cases using small trucks (S-C, S-R, and S-A).

In summary, the cases using smaller trucks (the cases S-C, S-R, and S-A) presented the largest amount of production while the lead time was also the longest. The case using larger trucks with drying operation (the cases L-R and L-A) produced the slightly less amount than the most productive case while the lead time was shorter. The case using larger trucks with no drying produced the least amount, but the lead time was almost as same as the deterministic case. The transportation flew smoothly without delay in this case. The way for improvement is, therefore, different by cases.



**Figure 2.** Relationship among the throughput, the work in process and the lead time; (a) in the cases S-C, S-R, S-A; (b) in the case L-C; (c) in the case L-R; and (d) in the case L-A.

#### 4. Discussion

The case L-C showed the shortest lead time and the smallest production amount. The queuing time of a truck is the shortest because the chip production started as soon as a truck arrives. The payload is less than planned because of the high moisture content, and it causes the longer idling time of chipper. Truck scheduling should be based on a weight basis if the payload of a truck is influenced by the material moisture content such as the cases using larger trucks.

Our previous study clarified that the reduction of MC to 30 WB% was necessary to use the full payload of a large truck in a Japanese case [26]. Since the total production in the cases with drying (the cases L-R and L-A) was larger, the reduction of MC is firstly recommended for the cases using larger trucks. The drying of material also plays an essential role in improving the calorific value of wood chip in wood chip production for fuel [27,28]. The result of any kind of analysis about woody biomass production for energy will surely indicate to promote the reduction of moisture content [29], but it was not in the cases using smaller trucks (the cases S-C, S-R, and S-A). Since the payload of a smaller truck is large enough to utilize the full volume capacity, the influence of MC did not appear. The unit of payment is on the weight basis in Japan customarily, but it should be on a calorific basis to make visible the influence of moisture content [28] in any situations.

Without the option of material drying, it is recommended for the case L-C to make frequent the truck arrival. According to the Equation (12), frequent truck arrival increases the work in process since it increases the queuing time of trucks, but reduces the idling time. The increase of work in process improves the throughput according to Equation (9). The more frequent truck arrivals increase the number of cycles  $i$ , and it causes more impact from the uncertainty as the queuing time of a truck [30]. The lead time is, therefore, longer when using smaller trucks (the cases S-C, S-R, and S-A) rather than when using larger trucks (cases L-C, L-R, and L-A). The punctuality of truck arrival is essential to improve the entire system efficiency [31].

For securing the punctuality of truck arrival, uncertainty should be eliminated as much as possible. In chipping productivity, the material volume is biologically defined, and the detailed inventory information is indispensable. In truck transportation, research and development in flexible trucking

systems are prosperous. Flexible trucking systems require real-time information and communication technologies [5] for optimization [31,32]. It requires massive investment and the sharing of needs and/or resources based on collaboration among stakeholders [33] while it is rarely fixed in time [34]. The result of this study enables a company to choose alternatives to secure the throughput by independent management means such as outsourcing or preparing buffer storage according to the estimated production loss as risk hedging [35]. The presented simulation method and results support the decisions such that a company should invest in real-time information and communication infrastructure or in buffering means.

Previous studies have already pointed out that the expansion of truck dimension improves the efficiency of truck transportation in terms of the cost [36,37], CO<sub>2</sub> emission, need of operators, and traffic on the roads [37]. Since this study focused on the impact of uncertainty on the stable supply of woody biomass, our result did not show the cost and CO<sub>2</sub> emission. It supports that the use of larger trucks has positive impacts on the need of operators and traffic on the road as it shows a smaller number of trucks. The shorter lead time is another advantage. The question is why the use of small trucks could achieve the highest daily production amount in this study. The answer is the capacity balance between chipping and truck arrival [37]. The uncertainty in MC influenced on the capacity of a large truck and this fluctuation interacted with the total production amount based on truck scheduling without considering the limitation by payload. As well as presenting an evaluation method of uncertainty in wood chip production for energy, this study presents an example of inefficiency of truck scheduling under uncertainty and emphasizes the importance of the capacity balance for an efficient wood chip supply chain [27,30,36].

To compare this result and the production loss observed in the actual supply chain, the method needs some improvements. This paragraph discusses the three limitations of this study. Firstly, this study used a general stochastic model as the interval of truck arrival assuming the arrival was Poisson process. The probability distribution of the interval of truck arrival might be different according to the company's strategy and the transportation conditions. It is necessary to categorize what kind of probability distribution can represent the interval from the real practices. Secondly, this study simulated production loss caused by idling time which was categorized as organizational delay [19] but the other two delays, mechanical and operator delays, were not considered. One of the mechanical delays is the stop for maintaining blade sharpness. It happens for sure since the dull blade of the chipper drops productivity [38]. It can be observed in field study and be modelled. Thirdly, the material drying has to be an optimal design [39]. It can bring economic and environmental benefits, which is sometimes possible even without investment [27]. In the cases among which there was no/slight difference such as the cases S-C, S-R, S-A, and L-A, the result from a cost optimization approach would help rational decision making on material drying.

## 5. Conclusions

The uncertainty in the supply chain undermines production. The daily production loss was quantified as ranging between 14% and 27% of the possible production amount which is simulated deterministically. The influence of uncertainty was also observed as the extension of the lead time, which indicates the system efficiency. The necessary improvements for system inefficiency sometimes cannot be implemented instantly due to the massive investment or the necessity of collaborative partnership. This simulation method can present alternative management which orients to gain income such as outsourcing or storing buffer, for example, based on the estimated loss of production.

This method can be applied for other operations interacting with each other called hot system such as log loading onto trucks. It uses the interval of truck arrival as the transportation parameter. One of the advantages of this method is simplicity in transportation modelling. For further development, the data of arrival interval should be collected by field studies and analyzed according to the transportation strategy and conditions. We must also include the other uncertainties causing mechanical and operator delays.



**Author Contributions:** Conceptualization, methodology, analysis, writing—original draft preparation, visualization, funding acquisition, M.Y.; writing—review and editing, supervision; K.T.

**Funding:** This research was funded by Japan Society for the Promotion of Science, Grant-in-Aid for JSPS Fellows 16J00623.

**Conflicts of Interest:** The authors declare no conflict of interest.

## References

1. Lautala, P.T.; Hilliard, M.R.; Webb, E.; Busch, I.; Richard Hess, J.; Roni, M.S.; Hilbert, J.; Handler, R.M.; Bittencourt, R.; Valente, A.; et al. Opportunities and Challenges in the Design and Analysis of Biomass Supply Chains. *Environ. Manag.* **2015**, *56*, 1397–1415. [[CrossRef](#)] [[PubMed](#)]
2. Japanese Forestry Agency. *Annual Report on Forest and Forestry in Japan, Fiscal Year 2018*; Japanese Forestry Agency: Tokyo, Japan, 2019.
3. Japanese Ministry of the Environment. *Kankyō, Junkangata Shakai, Seibutsu Tayousei Hakusho Reiwa Gannendo [Annual Report on the Environment, the Sound Material-Cycle Society and Biodiversity in Japan 2019]*; Japanese Ministry of the Environment: Tokyo, Japan, 2019.
4. Zandi Atashbar, N.; Labadie, N.; Prins, C. Modeling and optimization of biomass supply chains: A review and a critical look. *IFAC PapersOnLine* **2016**, *49*, 604–615. [[CrossRef](#)]
5. Acuna, M.; Sessions, J.; Zamora-Cristales, R.; Boston, K.; Brown, M.; Ghaffariyan, M.R. Methods to manage and optimize forest biomass supply chains: A review. *Curr. For. Rep.* **2019**, *5*, 1–18. [[CrossRef](#)]
6. Zandi Atashbar, N.; Labadie, N.; Prins, C. Modelling and optimisation of biomass supply chains: A review. *Int. J. Prod. Res.* **2018**, *56*, 3482–3506. [[CrossRef](#)]
7. Rönqvist, M.; D’Amours, S.; Weintraub, A.; Jofre, A.; Gunn, E.; Haight, R.G.; Martell, D.; Murray, A.T.; Romero, C. Operations Research challenges in forestry: 33 open problems. *Ann. Oper. Res.* **2015**, *232*, 11–40. [[CrossRef](#)]
8. Schuëller, G.I.; Jensen, H.A. Computational methods in optimization considering uncertainties—An overview. *Comput. Methods Appl. Mech. Eng.* **2008**, *198*, 2–13. [[CrossRef](#)]
9. Ghaderi, H.; Pishvaei, M.S.; Moini, A. Biomass supply chain network design: An optimization-oriented review and analysis. *Ind. Crops Prod.* **2016**, *94*, 972–1000. [[CrossRef](#)]
10. Wolfsmayr, U.J.; Rauch, P. The primary forest fuel supply chain: A literature review. *Biomass Bioenergy* **2014**, *60*, 203–221. [[CrossRef](#)]
11. Erber, G.; Kühmaier, M. Research trends in European forest fuel supply chains: A review of the last ten years (2007–2017)—Part two: Comminution, Transport & Logistics. *Croat. J. For. Eng.* **2018**, *38*, 269–278.
12. Asikainen, A. Chipping terminal logistics. *Scand. J. For. Res.* **1998**, *13*, 386–392. [[CrossRef](#)]
13. Flodén, J.; Williamsson, J. Business models for sustainable biofuel transport: The potential for intermodal transport. *J. Clean. Prod.* **2016**, *113*, 426–437. [[CrossRef](#)]
14. Röser, D.; Mola-Yudego, B.; Prinz, R.; Emer, B.; Sikanen, L. Chipping operations and efficiency in different operational environments. *Silva Fenn.* **2012**, *46*, 275–286. [[CrossRef](#)]
15. Yoshida, M.; Berg, S.; Sakurai, R.; Sakai, H. Evaluation of Chipping Productivity with Five Different Mobile Chippers at Different Forest Sites by a Stochastic Model. *Croat. J. For. Eng.* **2016**, *37*, 309–318.
16. Ghaffariyan, M.R.; Brown, M.; Acuna, M.; Sessions, J.; Gallagher, T.; Kühmaier, M.; Spinelli, R.; Visser, R.; Devlin, G.; Eliasson, L.; et al. An international review of the most productive and cost effective forest biomass recovery technologies and supply chains. *Renew. Sustain. Energy Rev.* **2017**, *74*, 145–158. [[CrossRef](#)]
17. Acuna, M.; Anttila, P.; Sikanen, L.; Prinz, R.; Asikainen, A. Predicting and controlling moisture content to optimise forest biomass logistics. *Croat. J. For. Eng.* **2012**, *33*, 225–238.
18. Watanabe, K.; Korai, H.; Kobayashi, I.; Yanagida, T.; Toba, K.; Mitsui, K. Estimation of Drying Time for Air-drying of Logs and Evaluation of Log Properties Affecting Drying Characteristics of Logs Using a Hierarchical Bayesian Model. *Mokuzai Gakkaishi* **2017**, *63*, 63–72. [[CrossRef](#)]
19. Spinelli, R.; Visser, R.J.M. Analyzing and estimating delays in wood chipping operations. *Biomass Bioenergy* **2009**, *33*, 429–433. [[CrossRef](#)]
20. Enkawa, T. *Gendai Operations Management—IoT Jidai no Hinshitsu, Seisansei Koujyo to Kogyaku Kachi Souzou [Modern Operations Management, Improvement of Quality and Productivity for Customers Value in the Era of IoT]*; Asakura Shoten: Tokyo, Japan, 2017; ISBN 9784254275704.

21. Talbot, B.; Suadiciani, K. Analysis of two simulated in-field chipping and extraction systems in spruce thinnings. *Biosyst. Eng.* **2005**, *91*, 283–292. [[CrossRef](#)]
22. Zamora-Cristales, R.; Boston, K.; Sessions, J.; Murphy, G. Stochastic simulation and optimization of mobile chipping and transport of forest biomass from harvest residues. *Silva Fenn.* **2013**, *47*, 1–47. [[CrossRef](#)]
23. Japanese Forestry Agency. *Heisei 12 Nendo Biomass Shigen no Riyo Shuhou ni Kansuru Tyosa Houkoku Sho [The Report on the Utilization of Biomass Resource in the FISCAL Year of Heisei 12]*; Japanese Forestry Agency: Tokyo, Japan, 2001.
24. Yoshida, M.; Sakai, H. Selection of chipper engine size based on business scale and optimised cost of chipping and transportation. *J. For. Res.* **2017**, *22*, 265–273. [[CrossRef](#)]
25. Team, R.C. *R: A Language and Environment for Statistical Computing*; R Foundation for Statistical Computing: Vienna, Austria, 2019.
26. Yoshida, M.; Son, J.; Sakai, H. Biomass transportation costs by activating upgraded forest roads. *Bull. Transilv. Univ. Brasov. Spec. Issue Ser. II For. Wood Ind. Agric. Food Eng.* **2017**, *10*, 81–88.
27. Laurén, A.; Asikainen, A.; Kinnunen, J.P.; Palviainen, M.; Sikanen, L. Improving the financial performance of solid forest fuel supply using a simple moisture and dry matter loss simulation and optimization. *Biomass Bioenergy* **2018**, *116*, 72–79. [[CrossRef](#)]
28. Gendek, A.; Nurek, T.; Zychowicz, W.; Moskalik, T. Effects of Intentional Reduction in Moisture Content of Forest Wood Chips during Transport on Truckload Price. *BioResources* **2018**, *13*, 4310–4322. [[CrossRef](#)]
29. Erber, G.; Kühmaier, M. Research trends in European forest fuel supply chains: A review of the last ten years (2007–2017)—Part one: Harvesting and storage. *Croat. J. For. Eng.* **2017**, *38*, 269–278.
30. Acuna, M.; Mirowski, L.; Ghaffariyan, M.R.; Brown, M. Optimising transport efficiency and costs in Australian wood chipping operations. *Biomass Bioenergy* **2012**, *46*, 291–300. [[CrossRef](#)]
31. Amrouss, A.; El Hachemi, N.; Gendreau, M.; Gendron, B. Real-time management of transportation disruptions in forestry. *Comput. Oper. Res.* **2017**, *83*, 95–105. [[CrossRef](#)]
32. Acuna, M. Timber and biomass transport optimization: A review of planning issues, solution techniques and decision support tools. *Croat. J. For. Eng.* **2017**, *38*, 279–290.
33. Scholz, J.; De Meyer, A.; Marques, A.S.; Pinho, T.M.; Boaventura-Cunha, J.; Van Orshoven, J.; Rosset, C.; Künzi, J.; Kaarle, J.; Nummila, K. Digital Technologies for Forest Supply Chain Optimization: Existing Solutions and Future Trends. *Environ. Manag.* **2018**, *62*, 1108–1133. [[CrossRef](#)]
34. Lehoux, N.; D'Amours, S.; Langevin, A. Inter-firm collaborations and supply chain coordination: Review of key elements and case study. *Prod. Plan. Control* **2014**, *25*, 858–872. [[CrossRef](#)]
35. D'Amours, S.; Rönnqvist, M.; Weintraub, A. Using operational research for supply chain planning in the forest products industry. *INFOR Inf. Syst. Oper. Res.* **2009**, *46*, 265–281. [[CrossRef](#)]
36. Sosa, A.; Acuna, M.; McDonnell, K.; Devlin, G. Controlling moisture content and truck configurations to model and optimise biomass supply chain logistics in Ireland. *Appl. Energy* **2015**, *137*, 338–351. [[CrossRef](#)]
37. Laitila, J.; Asikainen, A.; Ranta, T. Cost analysis of transporting forest chips and forest industry by-products with large truck-trailers in Finland. *Biomass Bioenergy* **2016**, *90*, 252–261. [[CrossRef](#)]
38. Nati, C.; Spinelli, R.; Eliasson, L. Effect of chipper type, biomass type and blade wear on productivity, fuel consumption and product quality. *Croat. J. For. Eng.* **2014**, *35*, 1–7.
39. Marques, A.; Rasinmäki, J.; Soares, R.; Amorim, P. Planning woody biomass supply in hot systems under variable chips energy content. *Biomass Bioenergy* **2018**, *108*, 265–277. [[CrossRef](#)]

