Scheduling Simulator by Ensemble Forecasting of Construction Duration

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Abstract –

As is well known, resident engineers on site might plan a heuristically deterministic construction schedule by PERT/CPM program. Since it is boring and time-consuming to gather, edit and input field data into the PERT/CPM program, however, there are very few opportunities to revise the construction schedule on daily works. This paper proposed an easy-to-use and -learning method to plan and revise construction schedule and to do ensemble forecasting construction schedule. First, this paper outlines this study and analysis methods to calculate daily real operational hour and rate based on 3-axis acceleration excited by machine operation. The 3-axis acceleration response values could be collected by sensor built in on-board smartphone for construction machine. In addition, the paper explains methods applied to the machine hour data and rate, to determine shape parameters of Beta distribution, to execute bagging based on samples from the Beta distribution, and to conduct ensemble forecasting of construction schedule. Finally, this paper discusses lesson learned from the empirical study and discussion of predictability of the ensemble forecasting of construction schedule.

Keywords –

Real operational hour and rate; LOESS; Hampel filter; Beta distribution; Ensemble forecasting

1 Introduction

As is well known, resident engineers on site plan heuristically deterministic construction schedule by PERT/CPM program. However, since it is boring and time-consuming to gather and edit field data into the PERT/CPM program, there are very few opportunities to revise construction schedule on day-to-day works.

Largely, scheduling construction schedule for mechanized earthworks are grouped into the following three types:

Type 1: Push works such as dozer operation, which means "make-to-stock process" in which the earthworks are not constructed based on actual demand,
Type 2: Pull works, which means "make-to-order process" in which the earthworks are cyclic distributions based on actual demand, for examples, LHD (Loading, Haulage, Dumping), concrete placement, etc., and
Type 3: Labour-intensive works such as reinforcement bar processing assembly, formwork assembly and disassembly, constructing slope frame, etc.

Due to limitation of space, our inquiring minds in this paper focuses on the Type 1 “dozer operation,” and proposals of easy-to-use and -learning methods to analyse and revise construction schedule and to do ensemble forecasting of the construction schedule. As for study on the type 2 and type 3, we intend to report at the ISARC 2021.

Here, we focus on automation as follows:

- Gathering and calculating data as to daily machine operational hours and rates,
- Repetitively calculating and learning on real operational rate sequence and pitch times for each of work-in days,
- Doing ensemble forecasting of construction schedule, and
- Generating infographics such as time series graph of real operational hour and rate sequence, and diagram of comparison between as-planned and as-built productions in order to grasp the current situations and evaluate the productivity.

This paper unfolds as follows:
First, this paper outlines this study on ensemble forecasting of construction schedule of mechanized earthworks. Secondly, this paper describes analysis methods being applied in this study, for example, LOESS (locally weighted scatter plot smooth) to capture time-series features, and Hampel filter to finding abnormal observations latent in daily real operational hour and rate sequence. In addition, the following methods are described:

- To determine shape parameters (alpha, beta) of Beta distribution, and

- To conduct bagging by samples from the Beta distribution, and do ensemble forecasting of construction schedule.

Thirdly, this paper provides empirical study on the above methods. Finally, this paper discusses lesson learned from the empirical study and discusses about possibility to detect features and abnormality latent in time-series of real operational hour and rate, and predictability of the ensemble forecasting of construction schedule.

2 Outline of this study

2.1 Overview of this Study

Image of dozer operation supposed in this study is shown in Figure 2.1.1.

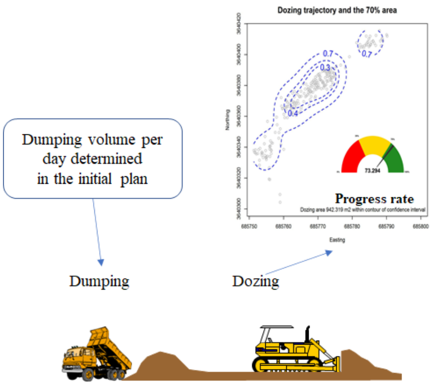

Figure 2.1.1. Image of dozer operation supposed in this study

In the dozer operation in Figure 2.1.1, readings of 3-axix acceleration, 3-axix angular velocity, and GPS position (latitude, longitude) are automatically gathered from on-board smartphone for dozer. And then, daily machine hour and rate could be automatically calculated from triaxial composite value of the 3-axix acceleration, Besides, as shown in top right of Figure 2.2.1, dozing trajectory and area could be visualized based on GPS data.

Generally speaking, M/M/c queueing theory might be applied to cyclic LHD operation. For simplicity and efficiency of discussion in this study, it is supposed that daily dumping volume is heuristically determined by the initial plan. Needless to say, dividing the day-to-day dumping volume by the dozing area on that day could give us the value of the thickness of embankment on that day.

2.2 Analysis Methods being Applied

This study supposes the workflow as shown in Figure 2.2.1 to analyse daily operational hour and rate and do bagging based on the Beta distribution, which is one of ensemble methods in machine learning, and to do ensemble forecasting of construction schedule.

Finishing ensemble forecasting of each of work types leads to PERT/CPM program. However, our inquiring minds focus on one dozer operation for embankment in this paper.

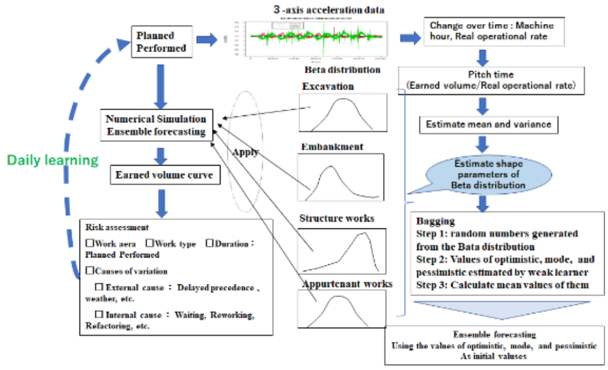

Figure 2.2.1 Workflow to analyse the dozer operation

Data collection and analysis methods applied in this study are described below.

1. Points on Construction(PoC)

The PoC takes sensor-based event detection approach to track a fleet, which is complement of construction machines, dump trucks and workers which are working together on site, and to automatically and real-timely gather a set of readings related to events occurred by the fleet activities as shown in Figure 2.2.2 [1],[2].

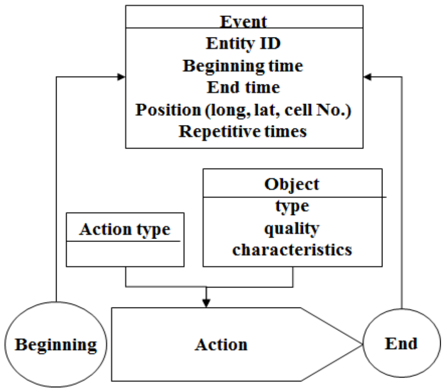

Figure 2.2.2. Image of sensor-based event detection approach

In this approach, construction machine behaviour from beginning to end could be automatically observed by sensors built in smart phone (e.g., 3-axial accelerometer, 3-axial angular velocity meter, GPS receiver, and communication module), and otherwise recognized by a button pressed event, that is, pushing predetermined function key on the smart phone by the operator. Construction machine has on-board smart phone whenever it is being operated. And then, the smart phone automatically sends the data set of readings via the Internet to store them into the database. Readings captured by the PoC consist of time, longitude, latitude, direction, speed, 3-axis acceleration, 3-axis angular velocity, and son.

2. Calculation of real operational hour and rate

Composition value of 3-axis acceleration is gained by

$$force = \sqrt{ax^2 + ay^2 + az^2} \quad (1)$$

,

where force: composition value, ax: lateral acceleration, ay: longitudinal acceleration, and az: vertical acceleration.

Figure 2.2.3 shows images of variance values of the forces by each of the dozer operations.

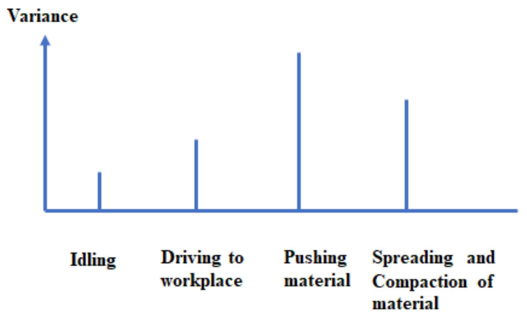

Figure 2.2.3 Images of variance values of the forces by each of the dozer operations

It is assumed here that variance values of force generated by idling and driving might be smaller than ones by pushing, spreading and compacting material. Therefore, events with time stamps, which have variance values of forces larger than the predetermined threshold, are extracted and then the operation hour could be calculated. In addition, dividing the daily operation hour sequence by the work hour on that day gives us the corresponding real operation rate sequence.

3. Bagging method

Bagging method is one of the ensemble methods in machine learning. The bagging often considers homogeneous weak learners, and learns them independently from each other in parallel and combines them following some kind of deterministic averaging process [3], [4].

Mean and variance of the averaged real operational hour and rate sequence determine shape parameter (alpha, beta) of Beta distribution, and then bagging by samples at random sampling with replacement from the Beta distribution would be executed

4. LOESS (locally weighted scatterplot smoothing model) [5]

The LOESS is a non-parametric approach that uses a weighted, sliding window and coverage to fit multiple regression in local neighbourhood. A weight is Tukey's tri-weight function as follows:

$$W(u) = \begin{cases} (1-|u|^3)^3 & |u| < 1 \\ 0 & |u| > 1 \end{cases} . \quad (2)$$

The weight sequence is defined by

$$w_i(x_0) = W\left(\frac{x_i - x_0}{h(x)}\right), \quad (3)$$

Incidentally, f(x) is approximated by a polynomial, that is, a quadratic approximation shown by

$$f(x) \approx \beta_0 + \beta_1(x - x_0) + \frac{1}{2}\beta_2(x - x_0)^2 \quad (4)$$
$$for\ x \in [x_0 - h(x_0), x_0 + h(x_0)]$$

To estimate $f(x_i)$, find the $\beta = (\beta_0, \beta_1, \beta_2)^T$ that minimizes

$$\hat{\beta} = \underset{\beta \in R^3}{\arg\min} \sum_{i=1}^{n} w_i(x_0)\left[Y_i - \left\{\beta_0 + \beta_1(x - x_0) + \frac{1}{2}\beta_2(x - x_0)^2\right\}\right]^2 \quad (5)$$

5. Beta distribution

As is well known, the mean of Beta distribution is given by:

$$\mu = \frac{\alpha}{\alpha + \beta} \quad (6)$$

If α > 1, β > 1, the mode by

$$m = \frac{\alpha - 1}{\alpha + \beta - 2}, \quad (7)$$

where m is the mode, and the variance by

$$\sigma^2 = \frac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)} . \quad (8)$$

In addition, relationships among mean and variance of data sequence, and shape parameters (α, β) of Beta distribution are represented as follows:

$$\alpha = \mu\left(\frac{\mu(1-\mu)}{\sigma^2} - 1\right) \text{ and} \quad (9)$$

$$\beta = (1-\mu)\left(\frac{\mu(1-\mu)}{\sigma^2} - 1\right) . \quad (10)$$

6. Ensemble forecasting of dozer operation schedule

Procedure of conducting ensemble forecasting of dozer operation schedule is shown below.

Step 1: When number of days elapsed becomes one third of process days of dozer operation, let put the day the 1st milestone, and the two third one the 2nd milestone. Calculate mean and variance of the real operation rate sequence at each of the milestones, and then specify the corresponding Beta distribution.

Step 2: Repeat n times to generate random number sequences with replacement from the Beta distribution.

Step 3: As for each of the random number sequences, calculate summary statistics that includes mean, standard deviation, variance, min, max, median, mode. and quantile.

Step 4: Average the summary statistics and then let put the 1st quantile be equal to optimistic, the mode be equal to most likely and the 3rd quantile be equal to pessimistic.
Step 5: To do ensemble forecasting, we would utilize the LOESS model, where each of the values such as optimistic, most likely and pessimistic are used as the initial value. And then ensemble forecasting should be executed from the 1st mile stone to the 2nd mile stone, and from the latter to the end of schedule

7. Quantitative performance indexes as to performance evaluation

The Performance index (PI) is depicted by coefficient of concordance, which is a ratio of the precedent rate to the successive one in each of work cells. The PI is given by:

$$PI = \frac{S}{P}, \tag{11}$$

where S is successive rate; P is precedent rate.

8. Detecting probably abnormal events

Probably abnormal events could be found by median absolute deviation (MAD). The absolute deviations from the median is absolute deviation around the median, which means a robust measure of central tendency, and is not sensitive to the presence of outliers. Besides, given a vector of data, find peaks in ranges of data that exceeds a set threshold. Hampel filter is utilized in this study [6]

3 Empirical Study

3.1 Outline of materials handled in this Empirical Study

Materials handled in this empirical study are dozer operation on river embankment construction, which outlines [7]:

1. The crown width is equal to 7m, the high-water level is equal to 10m, the free board of levee is equal to HWL+2m,
2. The front and back slope gradient is equal to 1:2 and 1:3, respectively, and the embankment length is equal to 877m,
3. The material of dike is sandy soil, and process days is equal to 91 days.
4. The dozer operation in the embankment works as follows:

- The earthmoving volume: 81,600 m3,
- The volume of dozer operation: 80,400 m3,
- The dozer class is 15 ton (D6),
- Number of dozers is equal to 3, and so Dozer volume per one dozer becomes equal to 2,800 m3.

3.2 Work Suppositions

Below are some more details on the work suppositions in this empirical study.

1. Let the embankment area be partitioned into the three work cells and focus on one dozer operation in one of the work cells.
2. Let rainy day, day off, etc. occur based on Poisson arrival

Let work out days be random number sequence generated by rpois (91, 0.28), and then we could gain number of work-in days "74" and umber of work-out days"17".
Therefore,

- The compacted volume per one dozer for a day is almost equal to 362 m3 (80,400/74/3), and
- The earthmoving volume by one dozer per a day is almost equal to 368 m3 (81,600/74/3).

3. Setting two milestones

Let set the 1st milestone at the point where one third of the process days intersects with 25% of the as-planned production volume and the 2nd milestone at the point where two third point of process days with 75% of the as-planned production volume. Here, we get the baseline curve, which goes along theses milestones, shall be utilized as reference line to compare with as-built production volume.

4. Handling work out days

Values at work-out day in pseudo-random number sequence of real operation rates are replaced by almost equal to zero, that is, sqrt(.Machine$double.eps)= 1.490116e-08;

5. Pseudo-real operation rate sequence

Let pseudo-real operation rate sequence be generated as follows:

- From beginning until the 1st milestone: the mean 0.3 plus rnorm(26,0,3)/100
- From the 1st milestone until the 2nd milestone: the mean 0.46 plus rnorm(27,0,2.5)/100, and
- From the milestone 2 to the end: the mean 0.4 plus rnorm(38,0,2)/100.

Let the pseudo real operational rate be regarded as hand-on real operational rate on site.

3.3 Pseudo-real operation rate sequence

Figure 3.3.1 shows pseudo-real operation rate sequence with the LOESS smoothing line and red cross marks detected by the Hampel filter as mentioned above.

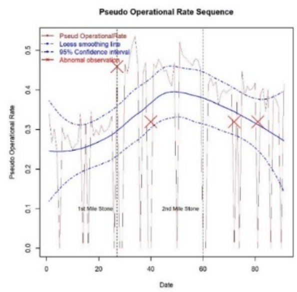

Figure 3.3.1 Pseudo-real operation rate sequence with LOESS smoothing line and red cross marks

Although the LOESS smoothing line shows time series feature very well, values at work-out day incline to push it down as a whole. Here, the sliding window width is 7.5. The smaller its value becomes, the more the predicted curve finely engraved along the original line graph. The red cross marks in Figure 3.3.1 means abnormal observations deviated from the median, which could be found by Hampel filter, where values on work-out days are replaced by the mean value of data sequence in order to avoid detection of ones on work-out days.

Figure 3.3.2 shows performance indexes as to the pseudo-real operation rate sequence. Similarly, the red cross marks in Figure 3.3.2 means abnormal observations deviated from the median.

As for the abnormal observations in both of Figure 3.3.1 and Figure 3.3.2, run length is not seen. Considering work suppositions here, probably, the causes of abnormal observations might be holiday, rain, machine failure, or something like that at the day before.

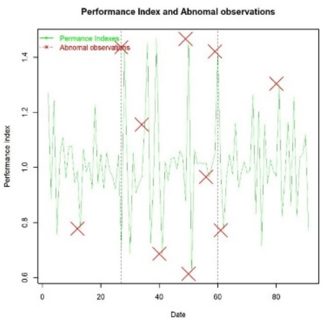

Figure 3.3.2. Performance indexes with probably abnormal observations

In daily construction control, the pseudo-real operation rate sequence with the LOESS smoothing line and observed abnormal ones might be drawn by each of work cells, leads to field inspection to explore the potential causes.

3.4 Productivity assessment

From our long experience in construction field, productivity by dozer operation is gained by the following equation.

$$Q=60*q*f*E/Cm \#(m3/hr) \text{ and} \quad (12)$$

$$Cm=0.027*L+0.55, \quad (13)$$

where Q： hourly production quantity(m3/hr), q： bank quantity per one cycle of dozing, f： soil conversion factor, E： work efficiency, and Cm：one cycle time.

Table 3.4.1 shows hourly production quantity by dozing (m3/hr).

Here, let put q=44 m3, f=0.9, E=0.8, L=50m, Cm=1.9 min, work hour per day=8 hr, and then t
Cm =1.9 and Q=1000.421 m3/hr are gained.

Applying the LOESS model as mentioned above to the data in Table 3.4.1 gives us productivity curves in Figure 3.4.1. Comparing actual productivity with the productivity curves in Figure 3.4.1 enables us to evaluate productivities for each the work sells.

Table 3.4.1 Hourly production quantity by dozing

Dozing	Sandy soil)		E=0.8
dist.(m)	Bank	Loose	Compacted
10	101	121	91
20	76	91	68
30	61	73	55
40	51	61	46
50	44	53	40
60	38	46	34
70	34	41	31
80	31	37	28
90	28	34	25
soil conversion factor	1	1.2	0.9

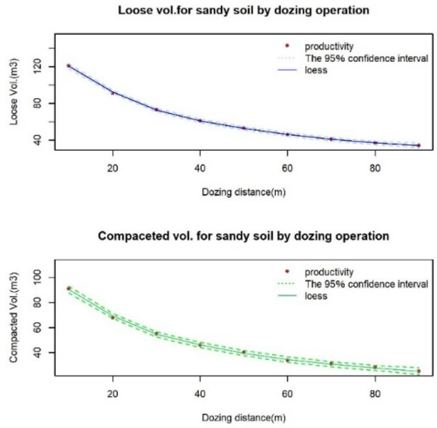

Figure 3.4.1 Productivity curves by the LOESS model

Multiplying the pseudo-real operation rate sequence in Figure 3.3.1 by the Q value gives the accumulative production sequence in Figure 3.4.2, which could be utilized as a reference line to compare with ensemble forecasting lines. Also, the accumulative production curve in Figure 3.4.2 shows speed of construction.

There are two important evaluation points of productivity, which are the 1st milestone and the 2nd milestone. It is very important to seriously grasp the actual states in each of work cells at the 1st milestone and to project work process toward to the 2nd one. In our bitter experience, problems latent in work progress incline to break out at the 2nd evaluation point, and then it might often compel us to rush-works.

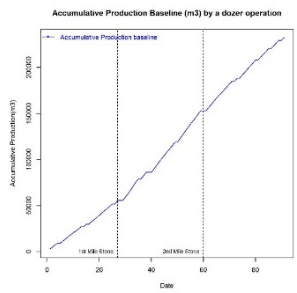

Figure 3.4.2 Accumulative production curve

3.5 Ensemble forecasting

Although doing the pessimistic, optimistic and most likely ensemble forecasting, respectively, this section reports the infographics on just the most likely one. That's why space did not permit us to insert the infographics on the pessimistic and optimistic ones.

3.5.1 Ensemble forecasting at 1st milestone

1. Shape parameters (alpha, beta) of Beta distribution

The equations (9) and (10) determine shape parameters (alpha, beta) of Beta distribution. From the descriptive statistics at the 1st milestone in Table 3.3.1, the mean "0.257" and the variance "0.014" give us B(13.382, 38.68).

2. Bagging method

At the 1st milestone, let repeat five times to extract 10,000 samples from B(13.382, 38.68) by random sampling with replacement, it leads to values at each of the five times the weak learner as shown in Table 3.5.1.1.

As described before, in the bagging method values at the weak learners are averaged. Table 3.5.1.2 shows the average of Table 3.5.1.1. Here, Let put

- 1st Qu=pessimistic,
- mode=most likely, and
- 3rd Qu=optimistic.

Table 3.5.1.1 Values at each of the five times the weak learner at the 1st milestone

	1st-	2nd-	3rd-	froth-	fifth-
Min.	0.00088	0.003006	0.00088	0.00088	0.001775
1st Qu.	0.161531	0.16108	0.163922	0.16458	0.160241
Median	0.262068	0.26198	0.262268	0.264431	0.264399
Mean	0.254653	0.254057	0.255458	0.256171	0.255417
3rd Qu.	0.353164	0.351715	0.352772	0.355252	0.354979
Max.	0.45866	0.458455	0.458458	0.458458	0.458458
Variance	0.013989	0.013904	0.0137	0.013822	0.01403
Mode	0.070389	0.416551	0.136546	0.334552	0.138386

Table 3.5.1.2 Average of Table 3.5.1.1

Min.	0.001059
1st Qu.	0.163119
Median	0.262625
Mean	0.255609
3rd Qu.	0.353726
Max.	0.458514
variance	0.013796
mode	0.207936

The most likely ensemble forecasting from the 1st milestone to the 2nd milestone are shown below.

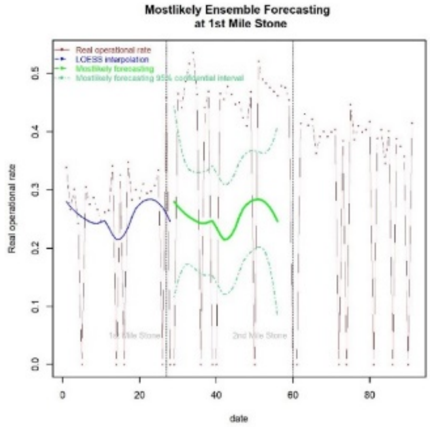

Figure 3.5.1.1 Most likely ensemble forecasting from the 1st milestone to the 2nd milestone

3.5.2 Ensemble forecasting at 2nd milestone

In the same way as mentioned above, let repeat five times to extract 10,000 samples from B(13.382, 38.68) by random sampling with replacement, it leads to values at each of the five times the weak learner at the 2nd milestone, and then average them. Similarly, the descriptive statistics at the 2nd milestone gives the mean "0.319" and the variance "0.03", and so the Beta distribution ~ B (6.9223, 14.7777)

The most likely ensemble forecasting from the 2nd milestone toward the completion are shown in Figure 3.5.2.1. The ensemble forecasting value is a bit larger than the determined production at the completion.

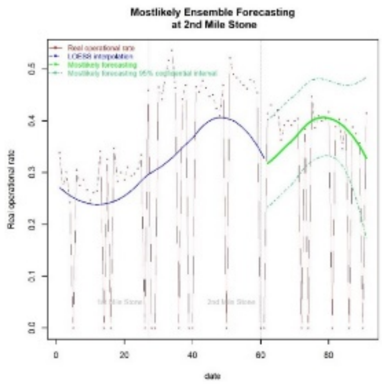

Figure 3.5.2.1 Most likely ensemble forecasting from the 2nd milestone to the completion

3.5.3 Comparison between Accumulative Production Baseline and Most Likely Ensemble Forecasting Line of Production

Figure 3.5.3.1 shows comparison between the accumulative production baseline in Figure 3.4.2 and the most likely ensemble forecasting line of production to the completion.

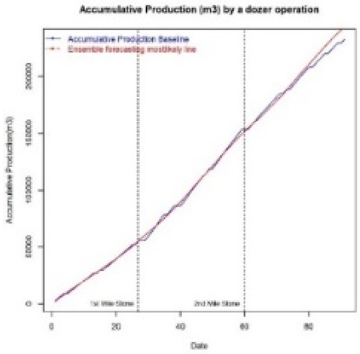

Figure 3.5.3.1 Accumulative production baseline and most likely ensemble forecasting line of production to the completion

4 Lesson Learned from Empirical Study

In this chapter, lesson learned from the empirical study is described and discussed.

As is well known, smoothing line method, for examples, simple exponential smoothing (SES), LOESS, and beta regression model, could show time-series features very well. The SES and the LOESS are non-parametric methods and could be easily handled without specific distribution. The LOESS could be easily used for extrapolate prediction. Whereas, the SES is not easily handled for extrapolate prediction. Beta regression model literally assumes Beta distribution. In many situations, scheduling problems assumes Beta distribution, and so the Beta regression model looks like to be more consistent than others. Concretely, GLM (generalize linear model) with logit function are used to the calculation of the Beta regression model. Incidentally it is prediction based on the logit transformed scale [7],[8]. However, relationship between logit distribution and Beta distribution is unclear.

Originally, interpolated prediction could be easier handled than extrapolated one. Therefore, with ensemble learning with the LOESS model, in other words, simulation-based ensemble forecasting in long term, is utilized in this study.

Although data analysis is generally expensive and time-consuming, the automatic analysis methods proposed in this study is easy-to-use and -learning and cost-effective for daily repetitive learning and automatically execute to find probable causes of unacceptable performance.

On-site usage of the ensemble forecasting method proposed in this paper forks two folds. The first is daily ensemble forecasting in short term, for example, ten-days productivity. The second is periodic ensemble forecasting in long term, for example, forecasting from the 1st milestone to the 2nd milestone, and from the 2nd milestone to the end. The second one is illustrated in the chapter three.

Figure 4.1 shows image of the ensemble forecasting for ten-days productivity. Work hack here is shown as below. As mention before, the hourly productivity "Q" by dozer operation is gained by the equation (12) and (13). During the first ten days from the dozer operation start, multiplying daily real operation rate in-suite gained from the PoC by the value "Q" could give the daily productivity by dozer operation, and then do ensemble forecasting for the first ten-days productivity.

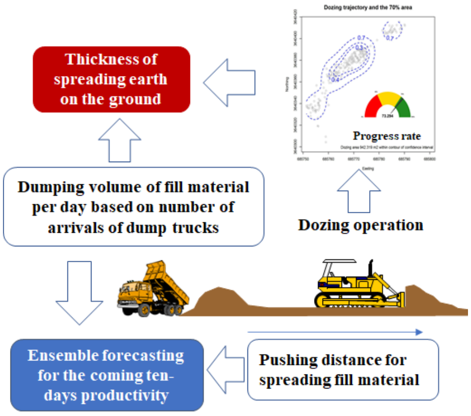

Figure 4.1 Ensemble forecasting for ten-days productivity

In the meantime, both of average of pushing distance for spreading fill material and dumping volume of fill material by the number of arrivals of dump trucks could be calculated by GPS data, and also the real operation rate in-suite could be gained from the PoC each day. And then the "Q" values could be gained on that day. Similarly, ensemble forecasting in the coming ten-days productivity could be executed. Moreover, these data could give us the dozer operation area, the thickness of spreading earth on the ground, and the progress rate to the target volume each day.

The above procedure enables us to repetitively do ensemble learning regarding scheduling of dozer operation, as considering environmental and ground condition.

It can be seen from the empirical study that show predictability of the ensemble forecasting of construction schedule. When watching transition of real operational rate sequence and finding abnormal observations as shown in Figure 3.3.2, the following matter shall be examined:

1. Appearance of new phenomena
2. Disappearance of existing phenomena
3. Sift change in mean and variance
4. Trend of increase or decrease

Looking around performance chart summary in each work cells and works backward from the 2nd to 1st milestones enables us to understand should-can-will-did works and to improve the working practices required from now on. On the other hand, looking ahead the ensemble forecasting at the 2nd milestones could inform us what the prospects are until the completion.

In practice, watching hand-on real operational rate sequences in each of work cells could give us information on which activities are most fragile and opportunities to examine resource allocation and reduction of lead time in each of work cells. Here, Infographics with early precautions (refer to ANSI 2535.5) such as charts, tables, and ensemble forecasting of construction schedule could provide a snapshot of work in progress over daily, weekly, bi-weekly or monthly.

These infographics would be automatically displayed on the dashboard of the remote real-time monitoring system [10]. These infographics would play a role in:

1. Thinking and decision-making support to:
- Provide workers with opportunities to recognize potential hazards, develop proactive countermeasures and start monitoring; and
- Pick a set of building block of information at the right level of abstraction and at the right time, and
- Stimulate or guide worker's creative thinking, i.e., indication or hint; and

2. Communication support to:
- Save or share information and mail back and forth to each other; and
- Help workers structure conversation and keep track of tasks.

The further development and research on this study are listed below:

1. Conducting hand-on verification and validation of the methods proposed in this study, and then we intend to report the results of this filed test at the ISARC 2021,
2. Applying M/M/c queueing theory to cyclic works such as LHD, concrete placement works, etc., and
3. Developing algorithm ensemble forecasting for each of work types including LHD and labour-intensive works, and integrated with PERT/CPM programs.
4. Cyber-agent, that is, computerized agent who work for ensemble forecasting of construction schedule. The cyber-agent here is a virtual engineer or line-manager who inhabit within a cyberspace composed of computer systems. The cyber-agent will passively or actively walk through the cyberspace to help workers explore and capture critical factors latent in a large amount of information that may go into making decisions [11].

In closing, we would like to say that any help and suggestions on this study would be heartedly appreciated.

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