

Prediction of MSW Long-term Settlement Induced by Mechanical and Decomposition-Based Compressions

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ABSTRACT: Long-term settlement of MSW landfills is a complex process, which is explained by the following two mechanisms: (1) the mechanical long-term compression of degradable organic solids (DOS) and un-degradable organic solids (UDOS); and (2) the decomposition-based compression of the DOS. Based on these two distinct settlement mechanisms, in this study, the authors propose a new estimation model to predict the long-term settlement of a MSW landfill. An optimization process using a real-coded genetic algorithm (GA) is performed to evaluate the parameters of the proposed estimation model, based on the settlement data measured at the Mountain View Landfill located near San Jose, California, USA. In comparison with the existing settlement models, the model predicts settlement very close to the measured data and closely conformed to the Grisolia and Napoleoni's long-term settlement curve. Unlike the existing models, it is the only model that can produce estimation for both long-term and short-term settlement reliably and consistently.

Key words : Municipal solid waste (MSW), Settlement estimation, MSW landfill, Landfill settlement, Genetic algorithm

INTRODUCTION

Landfills of municipal solid waste (MSW) often require additional considerations for proper development because of differential settlement, leachate generation, and landfill gas emissions. Among the practical problems of utilizing landfill sites, settlement may be the most significant concern from the perspective of a structural integrity of facilities or buildings built on landfill sites (Sowers, 1973; Morris & Woods, 1990).

MSW landfills suffer a large amount of long-term settlement, which is associated with the volume reduction caused by not only the mechanical compression of waste but also the biodegradation of organic components (Sowers, 1973; Chen, 1974; Al-Khafaji & Andersland, 1981; Wardwell & Nelson, 1981; Park & Lee 2002; Park *et al.*, 2007). It has been reported that the settlement of MSW landfills is attributed to the

following two mechanisms (Edgers & Noble, 1992; Sowers, 1973; Gordon *et al.*, 1986; and others): firstly, the immediate (or initial) mechanical compression is created due to an applied load and self-weight of the waste in the first few months following the completion of the landfill, and the mechanical long-term (or secondary) compression is produced due to the long-term reorientation of the particles, slippage at the particle contact, and delayed compression of the MSW constituents over a long time; and secondly, the decomposition-based compression is induced by a decrease in the volume of biodegradable organic solids due to the biological decomposition over several years. Grisolia and Napoleoni (1995) suggested a theoretical compressibility curve that considered the mechanical and biological compression characteristics as shown in Fig. 1. The settlement characteristics of MSW can be divided into five

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phases: (I) the initial settlement phase is induced by the self-weight of the MSW landfill and imposed loads; (II) the initial residual settlement phase is created by the compression of highly compressible solids; (III) the secondary settlement phase results from the creep of un-degradable organic solids (UDOS) and degradable organic solids (DOS) as well as the decomposition of DOS; (IV) the secondary settlement conclusion phase is where the decomposition of DOS slows down and is eventually completed; and (V) the final residual settlement phase continues due to the compression of the UDOS over a long time.

In this study, in order to model the complex long-term settlement of MSW landfills, where the settlement is induced by the mechanical long-term compression of DOS and UDOS as well as the decomposition-based compression of the DOS, a new estimation model is proposed based on a combination of the existing prediction models. To evaluate the parameters of the proposed estimation model, an optimization process using a real-coded genetic algorithm (GA) is performed based on the settlement data measured at the Mountain View

Landfill located near San Jose, California, USA, and its applicability is examined by comparing its performance with the existing settlement models’.

EXISTING MSW SETTLEMENT ESTIMATION MODELS

Various models have been proposed for the prediction of long-term settlement of MSW landfills based on the geotechnical and empirical background (Sowers, 1973; Yen & Scanlon, 1975; Edil *et al.*, 1990; Bjarngard & Edgers, 1990; Park & Lee; 1997, 2002; Park *et al.*, 2006). In this section, these models are reviewed and the specific parameters of the models are discussed.

Rheological model

Edil *et al.* (1990) applied the rheological model proposed by Gibson and Lo (1961) for long-term (secondary) compression to predict the long-term settlement of MSW landfills. The time-dependent settlement can be expressed as:

$$(1)$$

$$S / H_o = \varepsilon (t) = \Delta\sigma \cdot \{a + b(1 - \exp[-(\lambda/b) \cdot t])\} \\ = \Delta\sigma \cdot a + \Delta\sigma \cdot b(1 - \exp[-(\lambda/b) \cdot t])$$

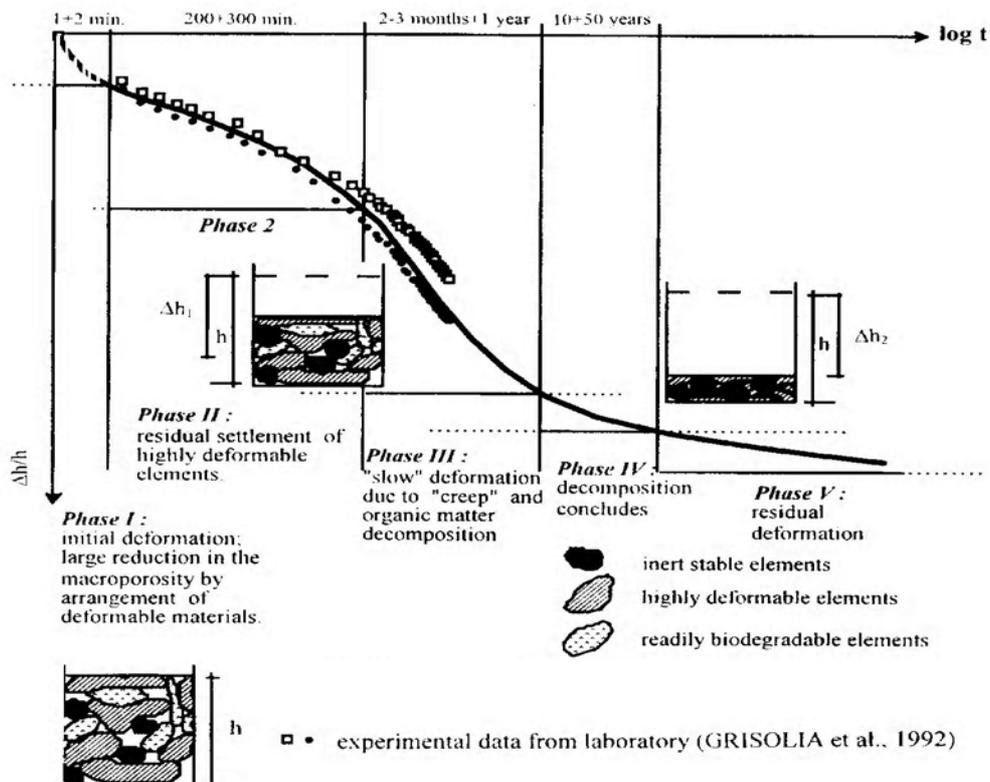


Fig. 1. MSW Compressibility Curve Due to the Mechanical and Biological Compressions (Grisolia & Napoleoni, 1995)

where S is the settlement (m), H_o is the initial height of the MSW landfill (m), $\varepsilon(t)$ is the strain, $\Delta\sigma$ is the compressive stress (kPa), a is the primary compressibility parameter (1/kPa), b is the secondary compressibility parameter (1/kPa), λ/b is the rate of secondary compression (1/day), and t is the time duration of interest (day). In Eq. (1), $\Delta\sigma \cdot a$ denotes the primary compression and $\Delta\sigma \cdot b$ refers to the ultimate secondary compression (i.e., as $t \rightarrow \infty$). The model uses a logarithmic plot of the strain rate versus time [$\log_{10}(\Delta\varepsilon/\Delta t)$ versus t]. The slope and intercept of the best-fit line yield the values of a , b and λ as follows:

$$\text{Slope of line} = -0.434 \cdot (\lambda/b) \quad (2a)$$

$$\text{Intercept of line} = \log_{10}(\Delta\sigma \cdot \lambda) \quad (2b)$$

Logarithmic function

Yen and Scanlon (1975) collected settlement data from several landfill sites and calculated the settlement rates as a ratio of change in the elevation of the platform to the elapsed time between surveys. The strain rate is represented in the following form:

$$m = \frac{1}{H_o} \cdot \frac{dS}{dt} = c - d \cdot \log t \quad (3)$$

where S is the settlement (m), H_o is the initial height of MSW landfill (m), m is the strain rate (1/month), t is the time duration of interest (month), and c and d are the strain rate parameters (1/month). The settlement of a given landfill for a time span of interest can be obtained as follows by integrating the strain rate over that period (Sohn & Lee, 1994):

$$S = H_o \cdot \int_{t_1}^{t_1+\Delta t} m \, dt = H_o \cdot \int_{t_1}^{t_1+\Delta t} (c - d \cdot \log t) \, dt = H_o \cdot \quad (4)$$

$$\left[c \cdot t - \frac{d}{\ln 10} \cdot (t \cdot \ln t - t) \right]_{t_1}^{t_1+\Delta t}$$

where t_1 is the median age of the fill at the beginning of the settlement computation period, Δt is the time span for which the settlement is computed. Because the settlement rate must be greater than zero it should be noted that the time span in the formula above should be limited to:

$$t_1 + \Delta t \leq 10^{(c/d)} \quad (5)$$

Biological model

Park and Lee (1997, 2002) assumed that the mechanical compression followed the linear pattern in the logarithmic time vs. strain, and the decomposition-related compression was characterized by first order kinetics as shown below.

$$\Delta S / H = \Delta\varepsilon_{mec} + \Delta\varepsilon_{dec} =, t_{bio} = t - t_c \quad (6)$$

$$C_{\alpha, mec} \log[(t + \Delta t) / t] + \varepsilon_{tot-dec} (1 - e^{-k t_{bio}})$$

where $\varepsilon_{tot-dec}$ is the total amount of compression due to the decomposition of biodegradable wastes; k is the compression rate due to decomposition; t_{bio} is the time lapse from the decomposition-based compression point (t_c). For fresh MSW landfills, t_c is assumed to be the time when the slope of settlement in the strain versus log-time plot becomes much larger. For old MSW landfills, however, it is not necessary to determine t_c because the biological strain has already occurred when the settlement monitoring begins. $C_{\alpha, max}$ is the rate of secondary compression for the mechanical secondary compression, which occurs due to the long-term slippage and delayed compression of some MSW constituents.

Hyperbolic function

In order to predict the long-term settlement of MSW landfills, Ling et al. (1998) applied the following hyperbolic function to the settlement data of three landfill sites:

$$S = \varepsilon(t) \cdot H_o = \frac{S_{uh}}{1 + S_{uh}/(\rho_o t)} \quad (7)$$

where S is the settlement (m), H_o is the initial height of the MSW landfill (m), $\varepsilon(t)$ is the strain, t is the time duration of interest (day), and S_{ult} is the ultimate strain (that is, as $t \rightarrow \infty$). Equation (6) can be transformed into a t/S versus t relation in order to determine the empirical parameters of ρ_o and S_{ult} . The following plot of versus produces a straight line, and slope and intercept of the best-fit line yield the values of ρ_o and , respectively:

$$\frac{t}{S} = \frac{1}{\rho_o} + \frac{t}{S_{ult}} \quad (8)$$

Power Creep Law Model

Edil et al. (1990) proposed a settlement model based on the Power Creep Law, which has been used to describe a time-dependent behavior of materials subject to a constant loading condition and to explain a creep behavior of many engineering materials.

$$S(t) = H \cdot \varepsilon(t) = H \cdot \Delta\sigma \cdot m \cdot (t/t_r)^n \quad (9-1)$$

where, m = reference compressibility, n = coefficient of compression, t_r = reference time, and $\Delta\sigma$ (kPa) = loading pressure.

RESULTS & DISCUSSION

The rheological model, logarithmic function, and hyperbolic function are mainly designed to predict only the mechanical compression characteristics of materials. Therefore they are not capable of estimating the settlement of MSW landfills, which results from the decomposition-based compression as well as mechanical compression of the wastes. The biological model only approximates the non-linear characteristics of the mechanical compression even though it handles well the biological compression. Therefore, these models are not appropriate to predict the long-term settlement of MSW landfills where settlement is caused by both the decomposition-based compression and the non-linear mechanical settlement. In this study, the authors propose a new model to estimate the long-term settlement of MSW landfills, which accounts

for those two different settlement mechanisms. The proposed model is formulated by combining (A) rheological models for the long-term mechanical settlement by DOS and UDOS and (B) the biological model for the decomposition-based compression.

Mechanical compression

Mechanical long-term compression occurs continually for several years after the completion of the initial compression due to the long-term reorientation, slippage, and delayed compression of DOS (e.g., paper and wood) and UDOS (e.g., chemically treated paper and leather). Note that, in this paper, inorganic elements such as rubber and compressible plastics are treated as UDOS due to their mechanical compressibility and biological un-degradability. The mechanical long-term compression of the DOS gradually decreases as the decomposition of the DOS begins, and it is completed when the decomposition of the DOS is completed. Eventually, only the mechanical long-term compression of the UDOS occurs continually over a long time. Thus, the mechanical long-term settlement due to the compression of the DOS and UDOS can be described by combining two rheological functions for the DOS and UDOS, respectively, as shown below:

$$\Delta\varepsilon(t) = \Delta\sigma \cdot \left[\begin{array}{l} b_{UDOS} (1 - e^{-k_{UDOS}t}) + \\ b_{DOS} (1 - e^{-k_{DOS}t}) \end{array} \right] \quad (9-2)$$

where $\Delta\sigma$ is the imposed loading (kPa), b_{UDOS} is the secondary compression coefficient of the UDOS (1/kPa), k_{UDOS} is the secondary compression strain rate coefficient of the UDOS (1/day), b_{DOS} is the secondary compression coefficient of the DOS (1/kPa), and k_{DOS} is the secondary compression strain rate coefficient of the DOS (1/day).

Decomposition-based compression

The estimation method developed by Park and Lee (1997, 2002) is used to consider the compression due to the decomposition of DOS. It assumed the compression process of biodegradable solid wastes due to the solubilization

from the decomposition is characterized by the first order kinetics as follows:

$$\varepsilon(t)_{bio} = \varepsilon_{tot-dec} \cdot [1 - e^{-k_{bio} \cdot (t-t_c)}] \quad (10)$$

where $\varepsilon(t)_{bio}$ is the compression induced by the decomposition of DOS at time t , $\varepsilon_{tot-dec}$ is the total amount of compression due to the decomposition of biodegradable waste, k_{bio} is the compression rate due to decomposition (1/day), and t_c is the starting point of decomposition-based compression.

PARAMETER EVALUATION OF THE PROPOSED METHOD

To predict the long-term settlement of MSW with the new settlement model composed of Eqs. (9) and (10), the unknown parameters, b_{UDOS} , k_{UDOS} , b_{DOS} , k_{DOS} , , , and , have to be determined on the basis of the curve-fitting of the measured settlement data. It is, however, a complex multi-dimensional parameter-fitting problem to find these variables, which requires an optimization process. The objective function for this optimization process is defined as the square of the difference between the measured settlement and the predicted settlement from the proposed settlement model as shown in the expression (11-1).

$$(11-1)$$

$$\text{Objective function, } ObjV = \sum_{i=1}^{Num} [S(i) - \hat{S}(i)]^2$$

$$\text{Constraint condition 1, } k_{DOS} = k_{bio}, \quad (11-2)$$

$$\text{Constraint condition 2, } k_{bio} > k_{UDOS}, \quad (11-3)$$

where Num is the number of measurement, $S(i)$ is the i^{th} measured settlement, and $\hat{S}(i)$ is the predicted value at the i^{th} measuring point.

As far as the constraint conditions are concerned for the model parameters, firstly, it is assumed that k_{DOS} is equal to k_{bio} , because the secondary mechanical compression of the DOS comes to an end when the decomposition-based compression

of the DOS finishes, as shown in the expression (11-2). Secondly, it was reported that the settlement due to the secondary mechanical compression of the UDOS continuously occurred in old MSW landfills (fill age, more than 40 years) whose decomposition-based settlement of the DOS was almost completed (Keene 1977; Stulgis *et al.*, 1995). This means that the secondary mechanical compression strain rate coefficient of the UDOS, k_{UDOS} is smaller than the decomposition-based compression strain rate coefficient of the DOS, k_{bio} , as shown in the expression (11-3).

This kind of multi-dimensional optimization problem only complicates the process of estimating the model parameters that can fit the measured settlement curve well. Some well-known optimization methods, such as Simplex, BFGS, and the quasi-Newton methods, produce either local or global solutions depending on how the initial values of the variables are set. Furthermore, as the number of optimization variables increases, the chance of the solution being converged locally rather than globally increases (Renders & Flasse, 1996; Leung & Wang, 2001). It is necessary therefore to apply a stable optimization technique that ensures the convergence to a global solution. The general acceptance is that a Genetic Algorithm (GA) is particularly suited to multidimensional global search problems where the search space potentially contains multiple local minima. GA is a stochastic optimization method based on the mechanics of natural genetics and natural selection that can be used to obtain global and robust solutions for optimization problems (Goldberg, 1989; Holland, 1975). Unlike the other search methods such as the Simplex method and the BFGS method, correlation between the search variables is not generally a problem. In this study, the real coded genetic algorithm (GA), known for its robust optimization (Goldberg, 1989; Holland, 1975), is used to ensure the convergence to global solutions, thereby avoiding the convergence to local solutions.

GA starts with a population of randomly generated chromosomes and advances toward better chromosomes by applying genetic operators, modeled on the genetic processes through

reproduction and mutation. After reproduction and mutation, the new population is created based on the previous individuals through a certain selection procedure. The selection procedure is conducted based on the fitness of each individual. In this paper, the rank-based fitness assignment is adopted in conjunction with the stochastic universal sampling. By using the rank-based fitness assignment, the best individual in each generation is ensured to be passed to the next generation. In addition, the process of adaptation is modified, where after performing selection, reproduction and mutation, a number of new individuals are always inserted to the population in every generation replacing old members in the population randomly. The number of the new individuals to be inserted is taken to be 10% of the population size. After adaptation process, the best individual in the final generation is chosen as the solution to the problem. Although there are many possible variants on the basic GA, the operation of a standard genetic algorithm is described in the following steps:

Creation of initial individuals

In contrast to binary-coding GA that uses binary string to represent design variable, real-coding GA uses vectors of real numbers to represent individuals as the candidates of design variables. If we decide to have q individuals in the population then for initialization we have to create the population of individuals as follows:

$$\begin{aligned} P^1 &= [a_1^1 \quad a_2^1 \quad a_3^1] \\ P^2 &= [a_1^2 \quad a_2^2 \quad a_3^2] \\ &\vdots \\ P^q &= [a_1^q \quad a_2^q \quad a_3^q] \end{aligned} \quad (12)$$

where a_j^i represents an element of the i th individual of the j th design variable.

Evaluation and selection

The objective function, the function to be optimized, provides the mechanism for evaluating each individual. Based on each individual's fitness, selection mechanism chooses mates for the genetic manipulation process. From the population, individuals are selected with rates proportional to

their fitness to yield an equality sized new population. The biological counterpart of selection is survival of the fittest. Selection yields a population with a higher average quality than the old population. Many selection methods exist, but the rank-based fitness assignment here used (Bäck and Hoffmeister, 1991). In the rank-based fitness assignment, the population is sorted according to the objective values. The fitness assigned to each individual depends only on its position in the individuals rank and not on the actual objective value. The reproductive range is limited, so that no individuals generate an excessive number of offspring. Ranking introduces a uniform scaling across the population and provides a simple and effective way of controlling selective pressure.

Reproduction

Reproduction involves randomly selecting two parents from the reproduction pool. These parents are then crossed to create offspring. We use intermediate recombination's technique to create offspring (Mühlenbein and Schlierkamp-Voosen, 1993). From two parent P_1 and P_2 , offspring are produced according to the following rule:

$$offspring = P_1 + \alpha \cdot (P_2 - P_1) \quad (13)$$

where α is scaling factor chosen uniformly at random over an interval $[-d, 1+d]$. Each variable in the offspring is the result of combining the variables according to the above equation with a new α value chosen for each individual.

Mutation

Selection can lead to a population with no more strings containing high-quality regions at different positions. If this is the case, the probability that reproduction leads to higher quality solutions will become too low, and improvement of the best solution within the population will stop. To prevent this premature convergence, the mutation operator is introduced. Mutation is able to generate most point in the hypercube defined by the variables of the individual and range of the mutation.

Analysis procedure

The selection, reproduction and mutation processes are performed iteratively generation per

generation. At the final generation, after proceeding the adaptive process, the best individual in the population is chosen as the optimum solution. In this paper, the adaptive process is slightly modified where after selection; crossover and mutation, a number of fresh individuals are inserted n every generation replacing the old member randomly.

The GA procedure used in this paper can be summarized as follows:

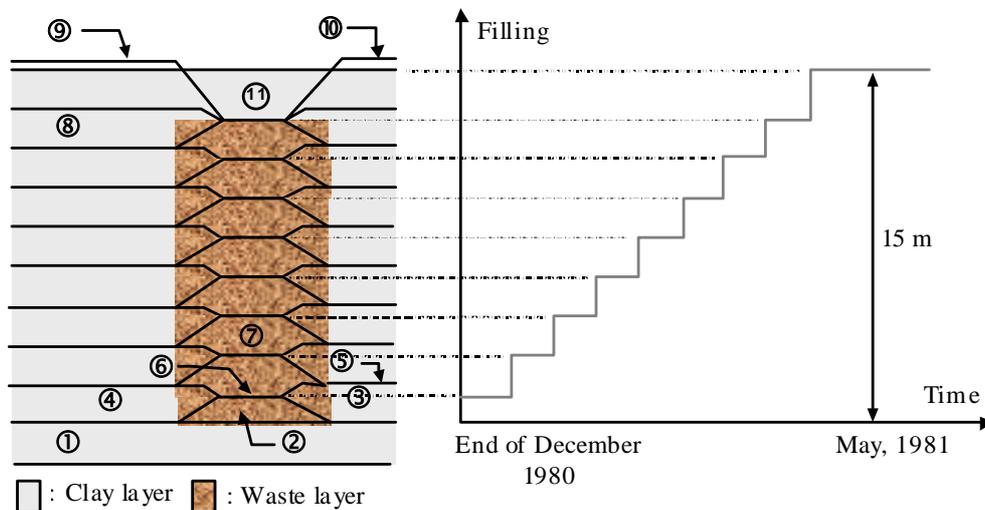
1. Initialize population of candidate individuals using real number chromosomes.
2. Evaluate the fitness of each individual according to the rank-based fitness assignment.
3. Based on the fitness, select individuals and place them in the mating pool according to the rank-based fitness assignment and stochastic universal sampling.
4. Do reproduction and mutation to the current population to create new individuals.
5. Insert a number of new random individuals replacing old individuals in the current population randomly. Make sure that the

inserted individuals did not replace the best individual in the population.

6. Evaluate the fitness of each individual.
7. Steps 3-6 are called a generation, and they are repeated until certain stop criterion is met. Typical stop criteria in a genetic algorithm run are a predefined maximum number of generations or an error smaller than a predefined value. In our genetic algorithm, maximum number of generations is used.

SETTLEMENT DATA OF THE MOUNTAIN VIEW LANDFILL

Numerous large-scale model cell laboratory tests and field scale tests have been conducted to investigate the settlement characteristics of MSW landfills (Rao *et al.*, 1977; Gandolla *et al.*, 1992; Wall, 1992; Kang *et al.*, 1995; Halvadakis *et al.*, 1988). Halvadakis *et al.* (1988) constructed 6 landfill cells at the Mountain View landfill located in San Jose, California, USA. Each cell, which was 30 m by 30 m with a depth of 15 m, was deposited in 15 layers, as shown in Fig. 2. and



1. Placement of 1.5 m compacted clay for ground water seal
2. Scarification of surface, placement of wet clay, and compaction with 824 Caterpillar compactor
3. Trimming of wall width of all loose or sloughed soil
4. Waste mixture placement to an approximate elevation of 0.45 m above cell wall surface
5. Buffer spread with front-end loader over compacted waste mixture (Cell A, B, C, and D only)
6. Waste mixture cleaned off surface of clay walls and surface sacrificed
7. Steps 2-5 repeated for eight lifts
8. Ninth lift/buffer placement prior to placing ninth lift of cell walls
9. Moisture application system installation on ninth lift surface and 1.5 cm pea-gravel cover
10. Placement of Hypalon cover over moisture application system and pea-gravel cover
11. Placement of ninth lift of clay cell wall over Hypalon providing gas-tight ruck.

Fig. 2. Landfill Cell Construction Details (Halvadakis *et al.*, 1988)

filled with the municipal refuse from San Francisco. The composition and the quantitative data of the refuse deposits in each cell are summarized in Table 1 and 2. The monitoring spanned over a period of approximately 4 years (1576 days). The parameters that were monitored included cell settlement, total volumetric gas production and gas composition (El-Fadel & Al-Rashed, 1998).

The settlement in each cell was monitored using 9 settlement plates installed in a diagonal direction over the cell surface. Fig. 3. shows the settlement characteristics of a typical cell. The settlement curves start out in a linear fashion at a relatively small angle up to approximately day 500. During a period of day 500 ~ 800, the settlement starts developing curves at a steeper

angle. The increased settlement rate is mainly attributed to the biological decomposition of organic components (Bjarngard & Edgers, 1990; Kang *et al.*, 1996, Park & Lee, 2002; Wardwell & Nelson, 1981). As shown in Fig. 3(a), the settlement data of cell B as well as cells D, E and F showed uniform settlement characteristics at nine settlement plates whereas cells A and C displayed uneven settlement characteristics at each plate as shown in Fig. 3(b). This non-uniform settlement patterns are likely related to the inconsistent preparation of the refuse for the cells and the inconsistent waste fill construction process. Additionally, the cell A experienced two cases of sudden settlement due to the excessive water supply. In this paper, therefore, analysis has been done using the settlement data of cells B, D, E and F.

Table 1. Compositions of the Refuse Deposits

Parameter	Cell A	Cell B	Cell C	Cell D	Cell E	Cell F
Refuse solid mass, kg	4,888	5,430	4,819	6,005	4,969	5,650
Void ratio	0.98	0.97	1.01	0.95	1.05	0.92
Porosity, %	50	49	50	49	51	48
Sludge solid mass, kg	151	129	66	0	55	0
Buffer solids mass, kg	10	10	9	10	0	0
Total solids mass, kg	5,053	5,569	4,894	6,015	5,025	5,650
Water mass, kg	2,643	2,683	2,115	2,147	2,106	2,023
Total mass, kg	7,696	8,252	7,009	8,161	7,131	7,674
Average water content (% of wet weight)	34	32	30	26	29	26
Average sludge to refuse solids ratio	0.032	0.024	0.014	0	0.011	0
Average buffer to water ratio	0.0036	0.0036	0.0043	0.0047	0	0
Cell volume, m ³	10,055	11,055	9,852	11,766	10,370	10,896
Cell density, kN/m ³	765	746	711	694	688	704
Precipitation	134	142	132	145	135	140
Added water, kg	1,700	0	1,700	235	238	0
Overall moisture content	46	32	44	28	31	26

Table 2. Decomposition Conditions of the Refuse Deposits

	Supply of Water	Leachate Recycled	Addition of Sludge	Addition of Buffer
Cell A	×	O	×	×
Cell B & C	×	×	O	O
Cell D & E	O	×	O	×
Cell F (Control)	×	×	×	×

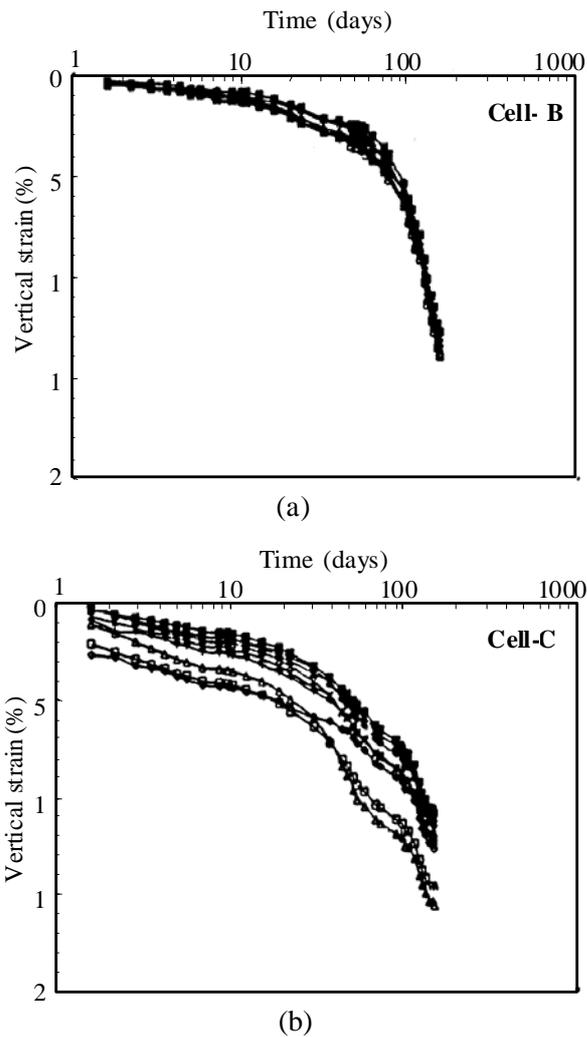


Fig. 3. Settlement Characteristics of the Mountain View Landfill

Parameter Estimation of the Proposed Settlement Prediction Model

In order to obtain the parameters of the proposed model, the real coded GA analysis was performed using the measured settlement data. A typical optimization process of the model parameters is shown in Fig. 4. where the settlement data of cell E was utilized. It is shown that the parameters started to converge to certain values at around the 50th generation. Therefore, in this paper, it is assumed that the model parameters have reached their respective convergence values after the 100th generation.

Table 3 shows the estimated model parameters by the GA analysis. The coefficients of the mechanical secondary compression for the UDOS and the DOS, b_{udos} and b_{dos} , are in range

of 0.11 ~ 0.14 m²/kN and 0.08 ~ 0.11 m²/kN, respectively, whereas the coefficient of the mechanical secondary settlement rate for the UDOS, k_{UDOS} , is in the range of 0.00013 day⁻¹ to 0.00055 day⁻¹. The total decomposition-based compression, $\epsilon_{tot-dec}$, is in the range of 15.7 ~ 19.5 % of the thickness of the cells. The coefficient of the compression rate due to decomposition, k_{bio} , is in the range of 0.00018 ~ 0.00064 day⁻¹. The decomposition-based settlement begins at between 51th ~ 850th day.

Table 4 shows the estimated settlement due to the mechanical compression and the decomposition compression with respect to the total thickness of each cell. The total mechanical compression settlement and the total decomposition-based compression settlement are 14 ~ 15.2 % of the thickness of the landfill cells and 15.7 ~ 19.5 %, respectively. Also the number of years taken for the 98% completion of the decomposition-based settlement (P_{bio}) is presented. The value of P_{bio} ranges from 18 years to 60 years.

Proposed Model Performance and its Comparison with the Existing Prediction Models

Based on the parameters through the GA optimization process, the proposed model has predicted the settlement for each cell as shown in Fig. 5. Each settlement prediction is very close to the measured data throughout the observation period. Additionally, as shown in Fig. 6. this predicted settlement closely conforms to the Grisolia and Napoleoni's long-term settlement curve (Fig. 1). which was described in Section 1. After the initial settlement (phase I), the initial residual settlement phase (phase II) is predicted due to the mechanical compression of the DOS and the UDOS, which is before the decomposition of the DOS occurs. As the decomposition increases, the secondary settlement phase (phase III) is predicted to have the combined settlement from the decomposition compression by the DOS and from the mechanical compression by the DOS and the UDOS. The secondary settlement conclusion phase (phase IV) is predicted, in which

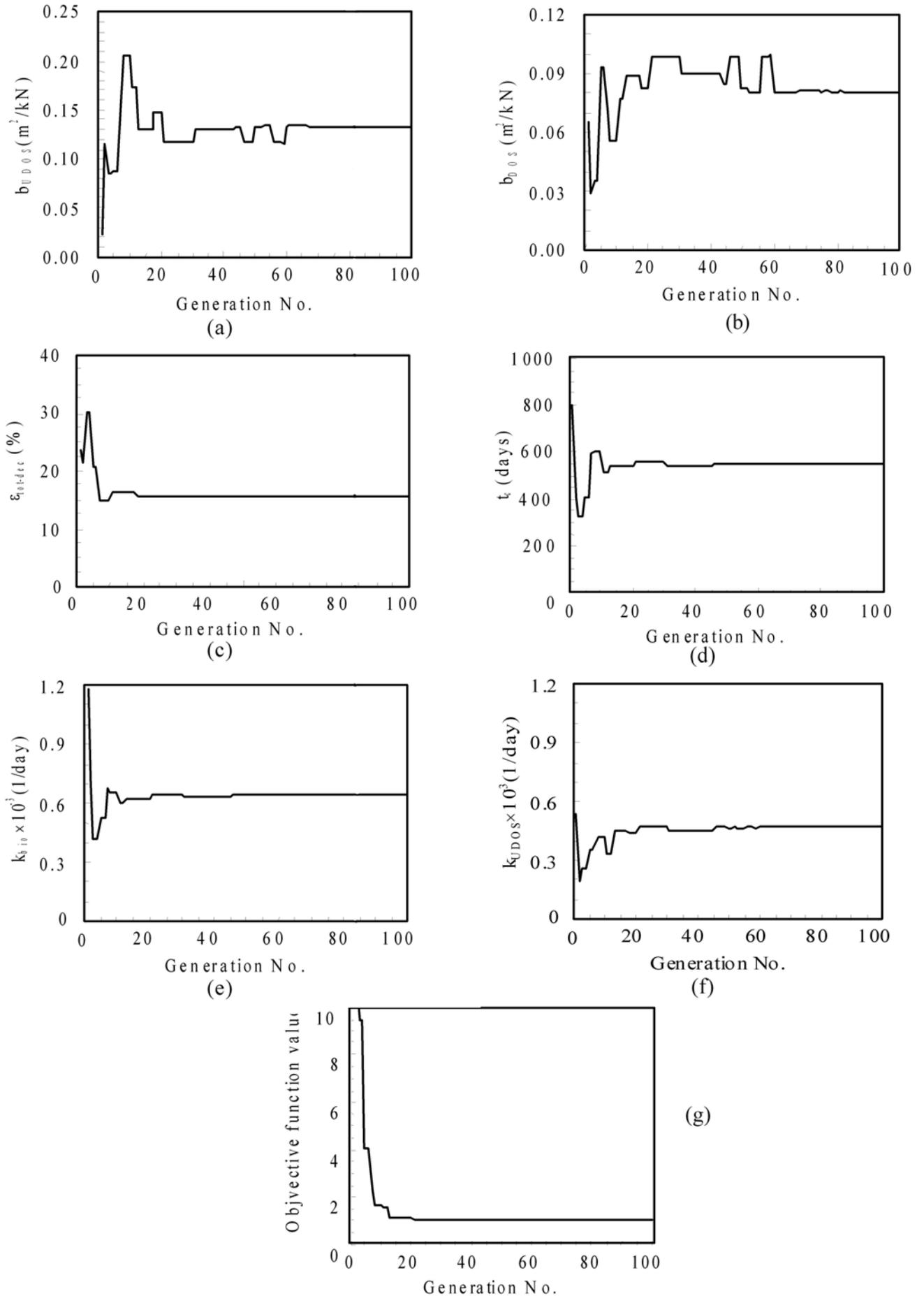


Fig. 4. Convergence of the Model Parameters and Objective Function

Table 3. Estimated Model Parameters from the GA Optimization Analysis

	Model Parameters related to Mechanical Compression Settlement				Model Parameters related to Decomposition Settlement		
	$\Delta\sigma$ (kN/m^2)	$b_{UDOS} \times 10^{-2}$ (m^2/kN)	$b_{DOS} \times 10^{-2}$ (m^2/kN)	$k_{UDOS} \times 10^{-4}$ (day^{-1})	$\epsilon_{tot-dec}$ (%)	$k_{bio} \times 10^{-4}$ (day^{-1})	t_c (day)
Cell-B	68.4	10.9	10.4	4.1	19.5	5.5	850
Cell-D	65.7	11.2	11.4	1.3	17.0	1.8	51
Cell-E	65.4	13.3	8.1	5.5	15.7	6.4	550
Cell-F	66.2	13.9	9.1	3.7	15.7	4.2	667

* $\Delta\sigma$ is determined based on the weight of the refuse and the surcharge

Table 4. Estimated Settlement by Mechanical and Decomposition Compressions

	Mechanical Compression Settlement (%)	Decomposition Settlement (%)	P_{bio} (years)
	$\Delta H / H$	$\Delta H / H$	
Cell-B	14.6	19.5	20
Cell-D	14.8	17.0	60
Cell-E	14.0	15.7	18
Cell-F	15.2	15.7	25

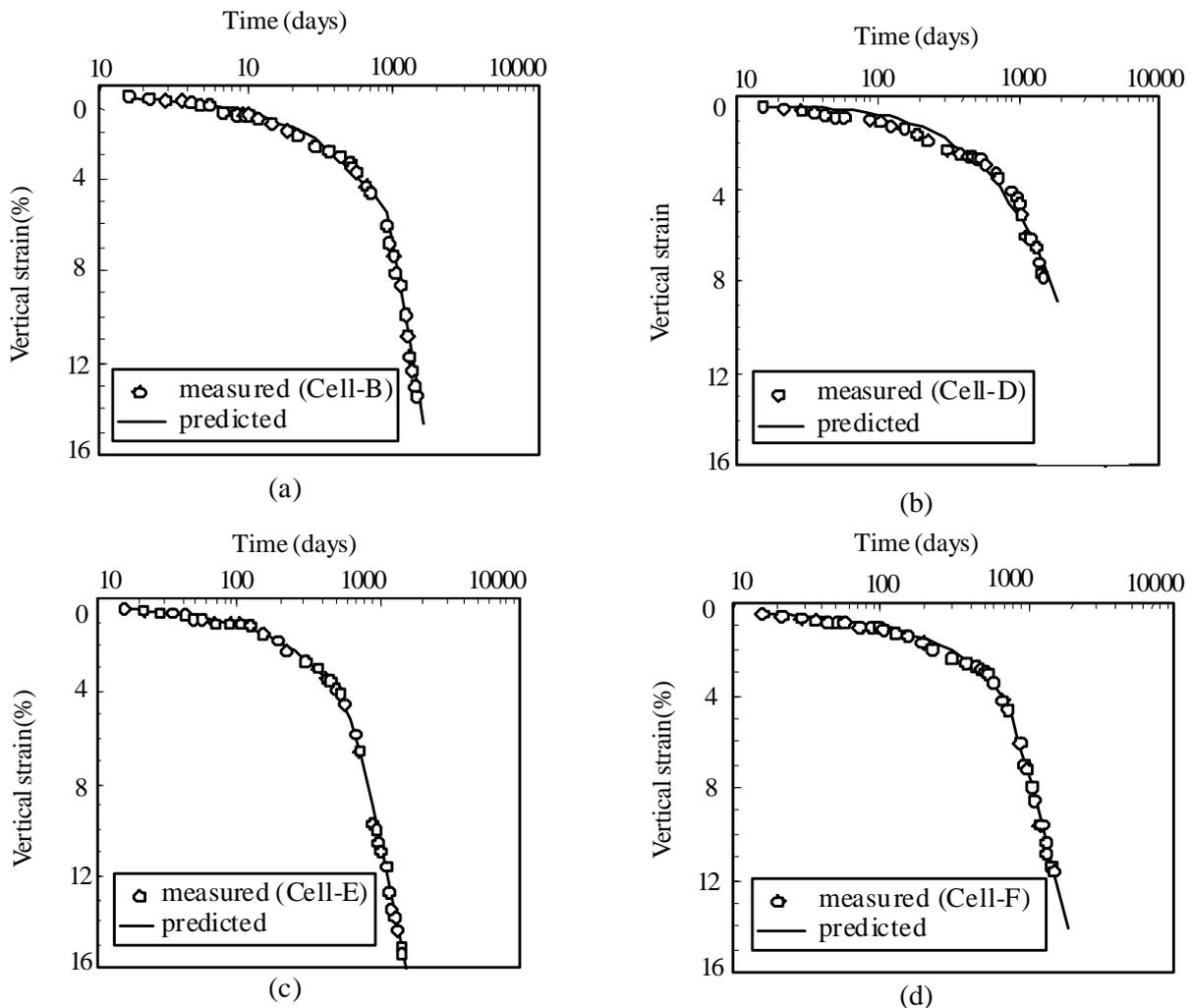


Fig. 5. Model Estimated Settlement vs. Measured Settlement

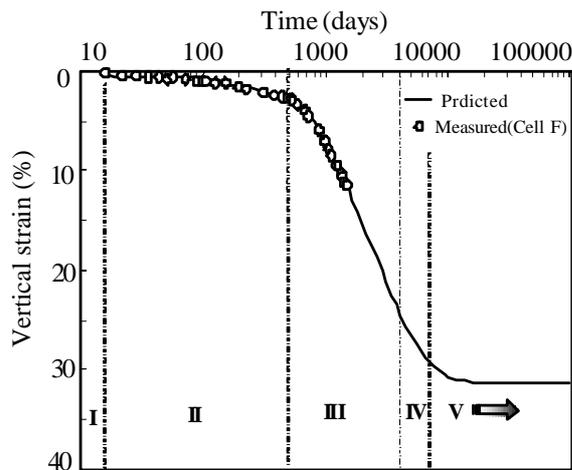


Fig. 6. Long-term Settlement Prediction and its Conformity to the Grisolia and Napoleoni's Long-term Settlement Pattern

the decomposition of the DOS comes to an end. The settlement is predicted to have the final residual settlement phase, where only the small amount of the mechanical settlement by the UDOS exists.

Fig. 7. shows the settlement comparison between the proposed model and the existing settlement models for each cell. The hyperbolic function, logarithmic function, and the rheological model predicted the settlement close to the Grisolia and Napoleoni's long-term settlement curve for Cell B and D as shown in Fig. (a) and Fig. (b), respectively. However, for Cell E in Fig. (c) and Cell F in Fig. (d), these models did not produce the similar settlement curves: they predicted the non-convergent settlement pattern and in some cases the settlement was overly estimated to a level that it was greater than the landfill depth. Therefore, the hyperbolic function, logarithmic function, and the rheological model did not provide consistent long-term settlement prediction. The Power Creep Law model failed to predict a converging settlement pattern in all the cells as shown in Fig. (a) ~ (d). It may be used, however, to predict short-term settlement of MSW landfill. As far as the biological model is concerned, the prediction could not be generated because the model parameters could not be determined from

the measured data. It is likely the model cannot be properly applied when the MSW has two active sources of settlement simultaneously from the mechanical compression and the decomposition-based compression, which is the phase III of the Grisolia and Napoleoni's curve in Fig. 1. On the other hand, in all the cells, the proposed model predicted settlement very close to the Grisolia and Napoleoni's curve as well as to the measured data. It is the only model that can produce estimation for both long-term settlement and short-term settlement consistently.

A similar observation can be made based on Table 5, which presents the prediction of settlement for 50 year duration for each cell. As shown, all the models except the proposed model showed a wide range of settlement prediction values. Considering all the cells had similar refuse composition as well as decomposition condition, unlike the prediction by the existing estimation models, the similar settlement values were expected as shown in the last column of the table for the proposed model.

CONCLUSION

In this paper, a new estimation model for the MSW long-term settlement was developed to overcome the limitations of the existing prediction models. The rheological model, logarithmic function, and hyperbolic function were mainly designed to predict only the mechanical compression characteristics of materials. Therefore they were not capable of estimating the settlement of MSW landfills resulting from the decomposition-based compression as well as mechanical compression. And the biological model only approximated the mechanical compression to be linear in a strain vs. log-time plot. By combining (A) the rheological models for the long-term mechanical settlement by DOS and UDOS and (B) the biological model for the decomposition-based compression, the proposed model was equipped to predict the long-term settlement of MSW landfills, which was caused by the decomposition-based compression and non-linear mechanical settlement.

To evaluate the parameters of the proposed estimation model, an optimization process using a real-coded genetic algorithm (GA) was performed based on the settlement data measured. The

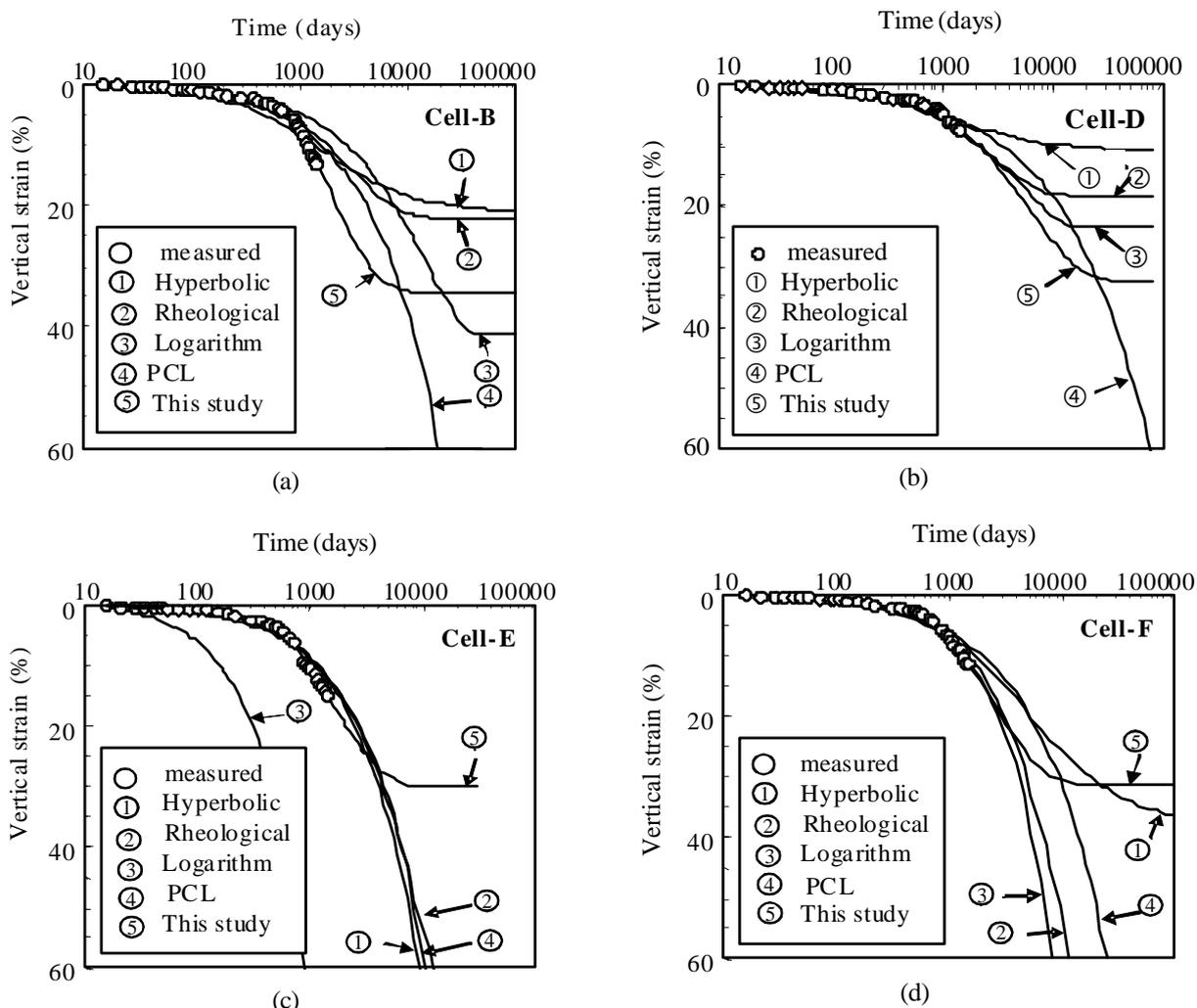


Fig. 7. Settlement Estimations by the Proposed Model and the Existing Models

Table 5. 50-year Settlement Prediction by Each Model ($\Delta H / H \times 100$)

	Hyperbolic function	Rheological model	Logarithmic Function	Power Creep Law	This Study
Cell-B	19.7	22.0	32.8	58.5	34.5
Cell-D	10.3	18.5	23.1	26.6	30.6
Cell-E	89.7	68.9	64.3	94.0	30.2
Cell-F	30.4	80.0	129.0	48.1	31.3

* ΔH = Estimated Settlement for 50 years, H = Depth of Landfill

proposed model predicted settlement very close to the measured data in all the cells. And the model's settlement prediction closely conformed to the Grisolia and Napoleoni's long-term settlement curve. On the other hand, the hyperbolic function, logarithmic function, and the rheological model did not provide consistent long-term settlement prediction by showing non-convergent settlement pattern in some cells. The Power Creep Law model failed to predict a

converging settlement pattern in all the cells, and the biological model's parameters could not be determined when the MSW had two active sources of settlement simultaneously from the mechanical compression and the decomposition-based compression. Therefore, the proposed model was the only model that was capable of producing estimation for both long-term settlement and short-term settlement in a consistent and reliable manner.

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