A Comparison of Three Completion Date Predicting Methods for Construction Projects

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This paper compares three different methods to predict completion date of construction project during construction stage. Construction project data are collected and analyzed to extract factors affecting project duration. A neural network model that includes conditions other than performance data is created to predict completion date; predicted results are then compared with those obtained from the methods based on earned value management (EVM) and earned schedule (ES). Factors affecting the project duration as input parameters of the neural network model are presented which are composed of continual and seasonal cycle data. The predicted results from the neural network application are more accurate and stable than those obtained from other methods compared in this study. The results can potentially provide early warning of schedule delay during the construction stage while the ES that describes schedule performance in units of time is more understandable than are units of currency as in the EVM method.

Key words: Neural Network, Construction Project, Duration Predicting, Earned Value, Earned Schedule

Time is the essence of a construction contract. Typically, a time period is specified as the contract duration. The contractor is obliged under the contract to achieve substantial completion within the specified period. Unfortunately, unexpected events can occur during the life of the construction project that affect the construction time necessary for the completion of work. Task and activity durations sometimes change because actual performance does not conform to plan. Additionally, unforeseen activities may need to be added and logic changes as a result of corrective actions to contain slippages as well as other planned changes also contribute to schedule modifications over time. When a contractor fails to complete the project within the contract period, delay becomes a reality of the project. Substantial effort on managing the construction process must be provided to achieve the objectives of completing the project on time and within budget while meeting established quality requirements and other specifications. This can not be accomplished without plan and control system. A control system periodically collects actual cost and schedule data and then compares them with the planned schedule to measure work progress and identify potential problems (Teicholz, 1993).

Predicting project performance is essential in tracking and control construction projects. Several methods have been proposed such as method based on earned value technique, fuzzy logic (Moselhi *et al.*, 2006), social judgment theory (Diekmann and Al-Tabtabai, 1992) and neural networks (Kasstra and Boyd, 1996). The earned value technique assumes in general either that the performance efficiency achieved up to the reporting date remains unchanged throughout the rest of the project, or that the performance will be as planned beyond the reporting date (Christensen, 1992, Fleming and Koppelman, 2000, Zwikael *et al*., 2000). However, the earned value method basically focuses on variances of cost and schedule in order to identify potential schedule slippage and areas of cost overruns. Moselhi *et al.* (2006) applied fuzzy logic to forecast potential cost overruns and schedule delays on construction project. The results of the methods are useful to assess the project status at certain times and to evaluate the benchmarks depicting profit efficiency of the project.

Time and cost are the two key parameters that play important roles in construction project management. Earned Value Management (EVM) has been wildly used to track both time and cost; the majority of the research has been focused on the cost aspect. However, different sources in the literature recently show that the classic earned value metrics fail in predicting the total project duration accurately (Lipke, 2003). Earned Schedule (ES) as an extension to the theory was introduced by Lipke(2003) to describe schedule performance in units of time.

This paper presents a comparison of three different methods: the proposed method based on neural networks, earned schedule, and earned value management, to predict the completion date of construction projects during the construction stage. The accuracy of each method is also compared and discussed. A neural network technique was used to develop the model to forecast the construction project since factors other than project performance data can be included into the model.

The main objective of a construction project is to successfully and qualitatively complete construction in the time required within the given budget. To achieve such objective, it is essential to have a good plan and control system. Since some uncertainty is inherent in any construction project, the actual quantity and cost will not be known until the end of the project. Organization representatives assigned to projects will measure actual quantity of each work item. Project performance reports will then be submitted to the head office on a periodic basis including forecast of the final budget and duration. In practice, predicting the final budget and duration of projects will start after a few months have passed since large variations early in the life of a project may exist. Project performance data, therefore, are crucial for managing cost and time and to help managers to understand the actual status of the project. The earned value method is commonly used as a tool to evaluate project status in term of schedule and cost variances compared with planned values that are normally based on a deterministic method like CPM (Chang, 2001). In the real world, there are, however, factors that greatly affect project performance such as traffic conditions, physical and weather conditions. These factors are not allowed as input data to the earned value method. The earned value method, therefore, may not be used separately to forecast the final cost and duration of a construction project. However, earned value is useful to identify the variance between planned schedule and actual performance. In terms of the project control perspective, if the project cost and duration from prediction tend to overrun and delay, action will then be taken to bring the project back on track.

Neural Network (NN) has been widely used as a tool in different aspects of construction such as estimating, planning, and productivity forecasting. The potential use of neural networks in construction was pointed out by Moselhi *et al*. (1991). Hegazy and Ayed (1998) developed a model to estimate road construction cost in Canada by considering project physical conditions and was concluded that there are ten parameters that affect road construction cost. Neural networks originated from a model of the biological structure of the human brain. Among various network architectures, back propagation (BP) networks learn from correct patterns and have gained wide application in engineering. A typical BP network has an input layer, output layer, and hidden layer. A mapping relationship between input variables and output variables will be explored during a training process. Designing BP network architecture includes determining the input and output variables (i.e., neurons in input and output layers) and selecting the number of hidden layers and neurons in each hidden layer. The training efficiency and the precision of prediction may be affected by the number of hidden layers and number of neurons in each hidden layer in a BP network. From a study of the literature, it was found that no definite criteria exist to establish a suitable number of hidden layers. Networks with different numbers of hidden layers and numbers of neurons in each hidden layer are investigated in the experiments. The network that can provide the most accurate prediction will be selected.

1. Input Analysis

The number of neurons in the input and output layers corresponds to the expected input and output variables of the problem. Output variables are the expected answers to the problem and the input variables are factors that affect the answers. Construction project data were collected from project progress reports to create a NN model to predict project completion date. The collected data are analyzed in order to find factors that might affect project duration. A process of selecting input variables is the most important step in developing the forecasting model. After experimentation with several NN models, it was found that five factors including work starting date, assessing date, contract duration, percent of as-planned completion, and percent of actual completion, greatly affect project duration. The best model to predict project completion date, shown in Figure 1, is composed of five neurons in the input layer and one neuron in the output layer while numbers of hidden neurons and hidden layers are explored during the training process.

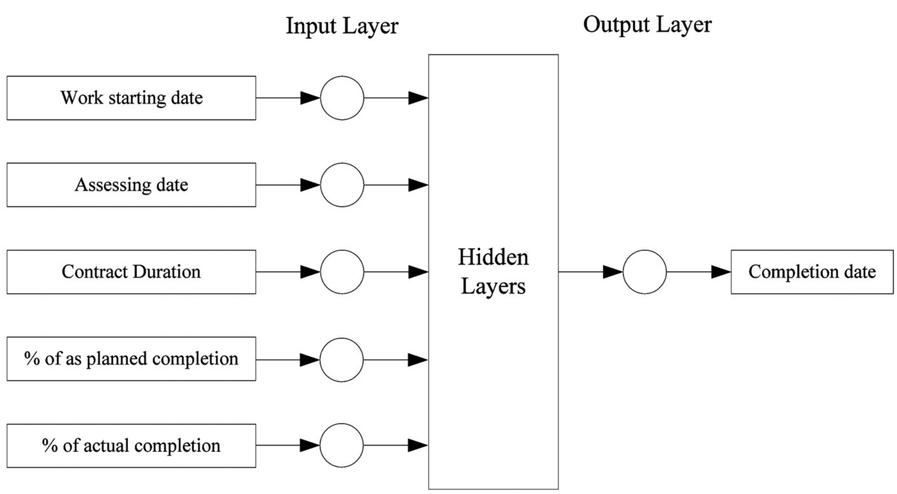

Figure 1 The NN model to predicting completion date

2. Training and Testing a Model

A total of 1,022 valid data patterns from 51 construction projects of the Department of Highways, for years between 2002 and 2007, were collected from project progress reports. Among them, 998 patterns were used for training from 49 projects, with a range of construction duration from 210 to 1,306 days. A network with two hidden layer and 300 hidden neurons have shown superior agreement to the training patterns. The obtained network was then tested with 24 data patterns from two projects. It should be mentioned that the test patterns must not participate in training. The comparisons between actual and predicted results are detailed in Figure 2, which shows that the trained network responds well to the 24 test patterns. The results show good agreement between actual and predicted results, with the mean absolute percent error (MAPE) for the testing patterns of 6.76%. The MAPE calculates the average of the absolute values of the difference between the forecast and actual values, expressed as a percentage of the actual value.

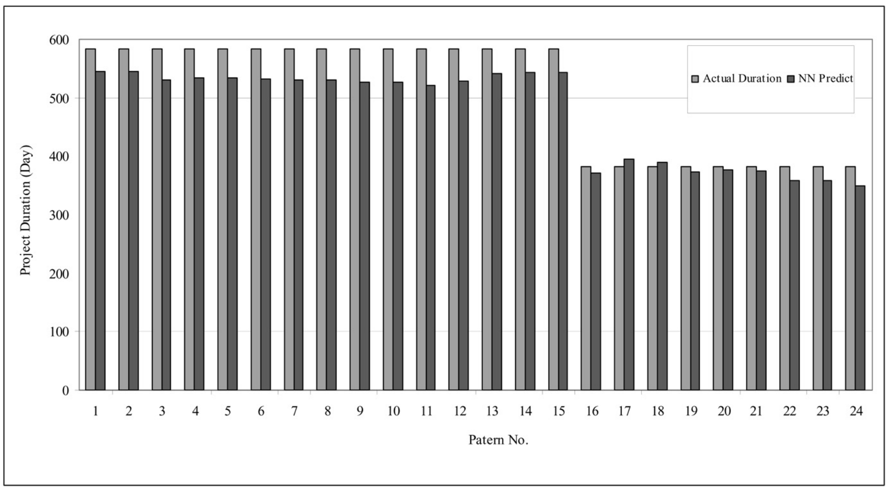

Figure 2 The actual and predicted project completion dates of the test patterns

Earned Value Management (EVM) emerged as a financial analysis specialty in United States Government programs in the 1960s, but it has since become a significant branch of project management and cost engineering. EVM allows the calculation of cost and schedule variances and performance indices and forecasts of project cost and schedule duration, as shown in Figure 3. It is generally true that past performance is a good indicator of future performance and as such Earned Value is a very useful tool for predicting the outcome of projects in terms of time to completion, cost to completion, and expected final cost. Although the classic earned value metrics are designed to forecast time and cost, the majority of these metrics are purely cost based. EVM was originally developed for cost management and has not been widely used for forecasting project duration.

There are three basic elements of EVM: 1) Planned Value (PV), also referred to as Budgeted Cost of Work Scheduled (BCWS). It is the total cost of the work scheduled /Planned as of a reporting date. 2) Actual Cost (AC), also referred to as Actual Cost of Work Performed (ACWP). It is the total cost taken to complete the work as of a reporting date. And 3) Earned Value (EV), also referred to as Budgeted Cost of Work Performed (BCWP). It is the total cost of the work completed/performed as of a reporting date. All three elements are captured on a regular basis as of a reporting date and then cost and schedule variances and performance indices and forecasts of project cost and schedule duration can be calculated. Project progress can also be measured.

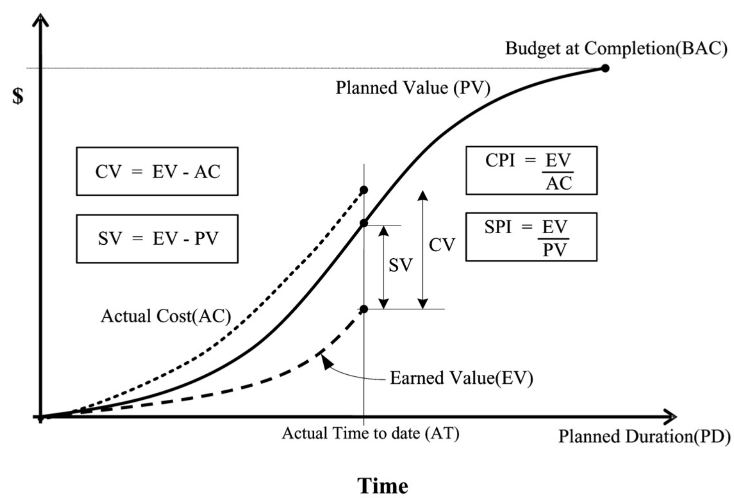

Figure 3 Earned Value Management Concepts

Four EVM duration forecasting techniques been applied over the last 40 years to predict project completion dates. These methods are generally considered to be accepted practice and have the same basic form, which is elapsed time (Actual time to date, AT) plus forecast for work remaining, as stated in Eq. (1). The work remaining term depends on work rate whereas the EVM provides four alternatives to calculate the work rate.

$$\text{Estimate at Completion Date (ECD)} = AT + \frac{(BAC - EV)}{\text{Work Rate}} \tag{1}$$

where as the work rate can be used any one of four options as below:

1) Average Planned Value (PV_{av})
2) Average Earned Value (EV_{av})
3) Current Period Planned Value (PV_{cur})
4) Current Period Earned Value (EV_{cur})

However, except for these four methods, project duration forecasting methods typically based on EVM indices have been purposed by Christensen (1992, 1996) and Fleming and Koppelman (1994, 2000). The twenty four identical data patterns used for testing the NN model were analyzed by the four EVM duration forecasting methods to predict project completion date. The results of each method were compared with actual duration, as presented in Table 1. It was found that estimated completion date (column 11) using work rate based on current period planned value provides the best results, on average, while predicted results obtained by using work rate in current period earned value show large variation against testing data.

Table 1 Project completion date using four EVM prediction methods

Project	BAC (1)	AT (2)	PV (3)	PV_{av} (4)	PV_{cur} (5)	EV (6)	EV_{av} (7)	EV_{cur} (8)	ECD(1) (9)=(2) + [(1)-(6)]/(4)	ECD(2) (10)=(2) + [(1)-(6)]/(5)	ECD(3) (11)=(2) + [(1)-(6)]/(7)	ECD(4) (12)=(2) + [(1)-(6)]/(8)
Project No.1	493845896	134	49,453,728	369,058	369,058	49,038,897	365,962	365,962	1,339	1,349	1,339	1,349
	493845896	165	65,859,289	399,147	529,212	68,318,641	414,052	621,927	1,231	1,193	969	849
	493845896	195	82,348,803	422,302	549,650	116,162,432	595,705	1,594,793	1,089	829	882	432
	493845896	226	99,554,394	440,506	555,019	130,632,116	578,018	466,764	1,051	854	880	1,004
	493845896	257	116,759,985	454,319	555,019	154,598,458	601,550	773,108	1,004	821	868	696
	493845896	287	134,172,992	467,502	580,434	195,528,406	681,284	1,364,332	925	725	801	506
	493845896	318	156,514,580	492,184	720,696	207,015,261	650,991	370,544	901	759	716	1,092
	493845896	348	183,715,612	527,918	906,701	232,270,540	667,444	841,843	843	740	636	659
	493845896	379	212,422,874	560,483	926,041	267,452,122	705,678	1,134,890	783	700	623	578
	493845896	410	249,905,777	609,526	1,209,126	300,366,951	732,602	1,061,769	727	674	570	592
	493845896	438	292,001,202	666,669	1,503,408	345,114,328	787,932	1,598,121	661	627	537	531
	493845896	469	338,501,731	721,752	1,500,017	371,342,483	791,775	846,070	639	624	551	614
	493845896	499	409,393,309	820,427	2,363,053	390,266,658	782,098	630,806	625	631	543	663
	493845896	530	484,561,593	914,267	2,424,783	436,416,557	823,427	1,488,706	593	600	554	569
	493845896	560	493,845,896	881,868	309,477	454,718,486	811,997	610,064	604	608	686	624
Project No.2	255067530	112	53,737,627	479,800	401,027	32,658,847	291,597	291,597	576	875	667	875
	255067530	142	84,919,633	598,026	1,039,400	35,671,194	251,206	100,412	509	1,015	353	2,327
	255067530	173	115,367,044	666,862	982,175	70,151,223	405,498	1,112,259	450	629	361	339
	255067530	203	142,621,010	702,567	908,466	112,061,369	552,026	1,397,005	407	462	360	305
	255067530	234	164,806,783	704,302	715,670	130,836,890	559,132	605,662	410	456	408	439
	255067530	265	186,775,750	704,814	708,676	153,466,481	579,119	729,987	409	440	408	404
	255067530	295	214,868,887	728,369	936,438	196,575,444	666,357	1,436,965	375	383	357	336
	255067530	326	240,679,171	738,280	832,590	221,291,488	678,808	797,292	372	376	367	368
	255067530	341	255,067,530	747,999	959,224	245,650,437	720,383	1,623,930	354	354	351	347

The concept of Earned Schedule (ES) was introduced by Lipke (2003) by expanding on earlier work by Fleming and Koppelman (2000), to describe schedule performance in units of time, as shown in Figure 4. It is an extension to the theory and practice of EVM. Henderson (2004) extended the concept of ES to include project duration forecasting and purposed two equations for forecasting the final duration for a project. In 2005, ES was designated as an "emerging practice" by the Project Management Institute.

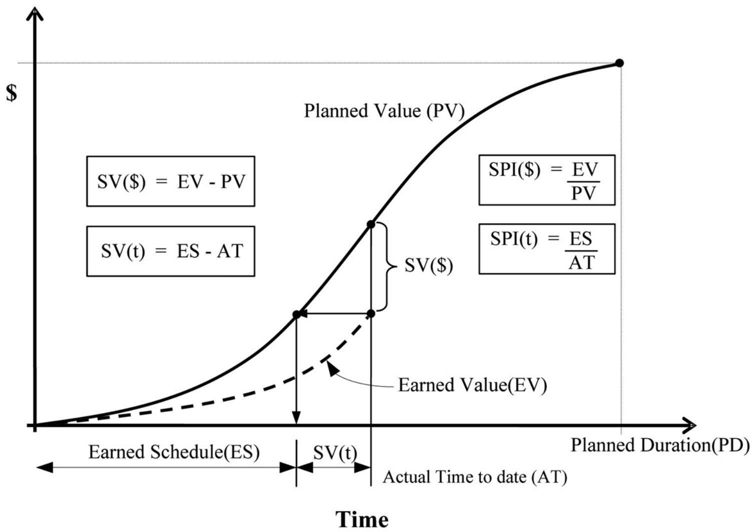

Figure 4 Earned Schedule Concepts

Traditionally, EVM tracks schedule variances not in units of time, but in units of currency (e.g. dollars) or quantity (e.g. labor hours). It is more natural to speak of schedule performance in units of time, but the problems with traditional schedule performance metrics are even deeper. Near the end of a project, when schedule performance is often the primary concern, the usefulness of traditional schedule metrics is demonstrably poor. The interpretation and the behavior of the EVM performance indicators SV and SPI over time have been criticized by Lipke (2003). First, the SV is measured in monetary units and not in time units, which makes it difficult to understand. Second, SV = 0 or SPI = 1 could mean that a task is completed, but could also mean that the task is running according to plan. Third, towards the end of a project, the SV always converges to 0 and the SPI always converges to 1, indicating a perfect performance even though the project is late. As a result, at a certain point in time the SV and the SPI become unreliable indicators, and this ‘‘grey time area’’ where these indicators loose their predictive ability usually occurs in the last third of the project. However, this is often the most critical period where the forecasts need to be accurate, since upper management wants to know when they can move on to the next project stage.

To correct these problems, Earned Schedule theory renames the two traditional measures SV and SPI as SV($) and SPI($), to indicate clearly they are in units of currency or quantity, not time. Then, time-based quantities SV(t) and SPI(t) are introduced. A stated advantage of Earned Schedule methods is that no new data collection processes are required to implement and test Earned Schedule; it only requires updated formulas. Earned Schedule theory also provides updated formulas for predicting project completion date, using the time-based measures, as shown in Eq. (2). Vandevoorde and Vanhoucke (2006) compared the traditional earned value performance indicators SV and SPI with the earned schedule performance indicators SV(t) and SPI(t). They found that the earned schedule method was the only method which showed satisfactory and reliable results during the entire project duration. Vanhoucke and Vandevoorde (2008) tested the performance of the three project duration forecasting methods and concluded that the earned schedule metrics outperform, on average, both the planned value method (Anbari, 2003) and earned duration methods (Jacob, 2004). Moreover, the studies reveal that the earned schedule method is more reliable in all stages (early stage, middle stage, and late stage) of the project life cycle.

$$\text{Estimate at Completion Date (ECD2)} = \frac{PD}{SPI(t)} \tag{2}$$

The same twenty four data patterns used for testing the NN model and analysis with the four EVM are applied in Eq. (2) to predict project completion datel The results were shown in Table 2.

Table 2 Project completion date using ES predicting methods

Project	AT (1)	PV (2)	EV (3)	ES (4)	SPI($) (5) = (3) / (2)	SPI(t) (6) = (4) / (1)	SV($) (7) = (3) - (2)	SV(t) (8) = (4) - (1)	ECD (9)
Project No.1	134	49,453,728	49,038,897	130	0.992	0.970	-414,831	-4	557
	165	65,859,289	68,318,641	170	1.037	1.030	2,459,353	5	524
	195	82,348,803	116,162,432	257	1.411	1.318	33,813,629	62	410
	226	99,554,394	130,632,116	280	1.312	1.239	31,077,722	54	436
	257	116,759,985	154,598,458	313	1.324	1.218	37,838,473	56	443
	287	134,172,992	195,528,406	360	1.457	1.254	61,355,414	73	431
	318	156,514,580	207,015,261	373	1.323	1.173	50,500,681	55	460
	348	183,715,612	232,270,540	396	1.264	1.138	48,554,929	48	475
	379	212,422,874	267,452,122	422	1.259	1.113	55,029,248	43	485
	410	249,905,777	300,366,951	443	1.202	1.080	50,461,174	33	500
	438	292,001,202	345,114,328	473	1.182	1.080	53,113,126	35	500
	469	338,501,731	371,342,483	484	1.097	1.032	32,840,752	15	523
	499	409,393,309	390,266,658	496	0.953	0.994	-19,126,652	-3	543
	530	484,561,593	436,416,557	510	0.901	0.962	-48,145,036	-20	561
	560	493,845,896	454,718,486	517	0.921	0.923	-39,127,410	-43	585
Project No.2	112	53,737,627	32,658,847	68	0.608	0.607	-21,078,781	-44	593
	142	84,919,633	35,671,194	76	0.420	0.535	-49,248,439	-66	673
	173	115,367,044	70,151,223	138	0.608	0.798	-45,215,821	-35	451
	203	142,621,010	112,061,369	170	0.786	0.837	-30,559,641	-33	430
	234	164,806,783	130,836,890	198	0.794	0.846	-33,969,894	-36	425
	265	186,775,750	153,466,481	218	0.822	0.823	-33,309,269	-47	438
	295	214,868,887	196,575,444	276	0.915	0.936	-18,293,443	-19	385
	326	240,679,171	221,291,488	303	0.919	0.929	-19,387,683	-23	387
	341	255,067,530	245,650,437	332	0.963	0.974	-9,417,093	-9	370

To compare the accuracy of each prediction method, the predicted results obtained from each method presented above are compared with the actual project duration. Results are shown in Figure 5 for project 1 and in Figure 6 for project 2. The EVM estimated completion date using work rate based on current period planned value was used in comparison since it provided better results. The MAPE and the mean absolute deviation, MAD, were used to measure the accuracy of each predicting method. The MAD is used to measure the average absolute deviation of observations from their forecasts. The MAPE and MAD of each forecasting result are summarized in Table 3. The MAPE and MAD values indicate that,the NN method provides the most accurate prediction among the methods studied. The ES method yields more accurate results than those obtained from the EVM method for project no.1, while the EVM method gives better predictions than those acquired from the ES method for project no.2.

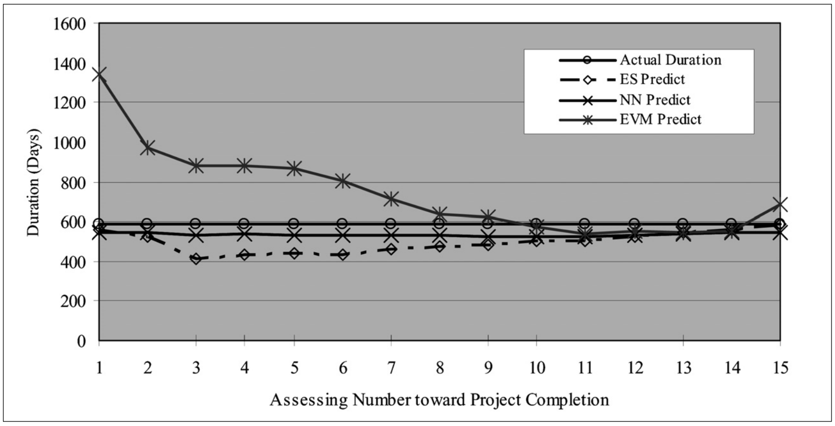

Figure 5 Comparison of predicted and actual duration of Project No.1

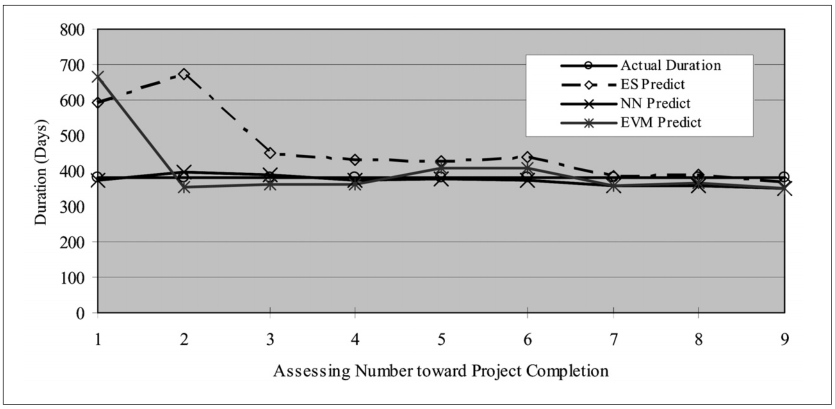

Figure 6 Comparison of predicted and actual duration of Project No.2

Table 3 Accuracy of the results obtained from the prediction methods

Testing Project	Project No.1	Project No.2
No. of test patterns	15	9
Actual Duration(day)	584	382
Mean ES Predict(day)	496	461
MAPE (%)	15.17	21.47
MAD(day)	89.00	82.00
Mean EVM Predict(day)	744	404
MAPE (%)	31	14
MAD(day)	182	53.00
Mean NN Predict(day)	534	372
MAPE (%)	8.51	3.84
MAD(day)	49.67	14.67

Figure 5 and Figure 6 show that the accuracy of the forecasts for both the projects obtained by the NN method is very stable over the course of the projects compared with those obtained from the EVM and ES methods. The accuracy tends to increase as the project duration advances. However, large variations in the early life of the two projects still exist, especially in project no.2, even though the first four assessing periods were omitted as suggested by the Department of Highway to avoid such variation.

This variation occurs because the predicted results of both ES and EVM methods are based on work rate, which is very low in the early stage of the project, exhibiting the characteristic s-curve. Since the work rate is low in the early stage, the project appears to take longer to complete. Once the project has reached roughly one-fourth of its planned duration, the work rate picks up, resulting in better predicted outcome and getting closer to the actual project duration. Project no.1 was ahead of schedule, while project no.2 was behind schedule, as illustrated in the Table 2. As a result, using the EVM and ES methods to predict completion date can be concluded that the project duration tends to decrease if the project is ahead schedule and tends to increase if the project is behind schedule. Consistent with traditional EVM, the metrics are good at the beginning of a project and show schedule performance trends but they do not reflect real schedule performance at the end. As they advance toward completion, its SV and SPI converge to 0 and 1, respectively. That may not reflect actual performance at the end of the project. However, for the owner's perspective, the SV and SPI can be effectively used to control budget and schedule according to plan because an owner has obligation to pay a contractor amount of money as specified in the contract. But from the contractor's point of view, the SV and SPI will become unreliable indicators during the last third of the project as pointed out by Lipke (2003). Therefore, the contractor should switch to the earned schedule method for monitoring project progress in the final stage of the project. The ES method can be easily integrated into an existing management system since it needs no additional information to provide forecasts. An early warning of project problems can be highlighted so that corrective action can be taken.

This paper presented a comparison of three different methods to predict completion date of construction projects during the construction stage. First, a neural network model was applied for predicting completion date of construction projects It was found that five factors including work starting date, contract duration, percent of as-planned completion, and percent of actual completion, greatly affect project completion date. Second, four EVM duration forecasting methods were used to predict project completion date. It was found that the predicted results using current period planned value as work rate provide better accuracy against testing data. Third, the ES method was used to predict the same parameters. The prediction results of all three methods are compared. The predicting results obtained from the NN model were more accurate and very stable for project completion date forecasting.

The ES method presented better results than those obtained from EVM method. An advantage of the ES is that it describes schedule performance in units of time rather than units of currency as in the EVM. It is also valuable in the last third of the project, when schedule performance is often a crucial concern. The NN method not only can give construction manager with better forecasting results to manage the projects but also provide accurate information. The possibility of schedule delays can also be determined using forecasting results and target plan. The EVM method, however, is still very helpful in managing construction projects particularly in cost control, since it is used to measure and communicate the real physical progress of a project.

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