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Practical Prediction of Overall Performance from Formative Assessment Results of Engineering Students*

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In this paper, a new model was employed for probabilistic prediction of overall performance of engineering students. The model employs formative assessment results to estimate the summative assessment mark of an individual student. In the present study, statistical evaluation of predictions was conducted using data of seven (7) examination events involving 441 students studying bachelors and master's degrees of civil engineering programmes. The other key variables of the data comprised different class sizes, and heterogeneous classes containing students of varied academic performance levels. It was found that the model gave realistic predictions with a good to excellent level of accuracy. The range for summative performance results of students whose formative assessment marks fall between 50 to 70%, can be accurately estimated. The model may be used to inform policy frameworks targeted at promoting students' performance and throughput.

Keywords: prediction model; formative; summative assessment; examination

1. Introduction

Progress of students towards achievement of learning objectives set out at the beginning of module teaching, is typically monitored using formative assessments. Accordingly, assessment data are compiled throughout the module's teaching duration over the semester or year. For students, these data may provide the information and/or course of action needed for him/her to sustain or improve learning achievements towards mastery of the subject. Instructors also employ these data to improve module delivery for betterment of students' performance. Assessments involve the administration of assignments, tests, examinations etc. needed to determine the performance of students for purposes of deciding academic progression [1, 2].

1.1 Current Perspectives and Developments on Assessment Approaches

In the earlier associated paper [3], reports from various literatures are discussed showing that significant correlation exists between *formative* versus *summative* assessment results at higher or tertiary level of education [4–7]. Later in Section 2.0 of this paper, further discussion is given on components of each assessment type. Engineering studies in most higher education institutions (HEIs) employ a system of integrated formative and summative assessments, following recommendations from earlier research studies of 1960's to 1990's that led to policy changes worldwide, as elaborated by Looney [8].

Even prior to the COVID-19 pandemic, there was a shift in emphasis towards the importance of formative assessments on grounds that this type of assessments aid students in developing learning skills [9], through utilisation of feedback mechanisms provided during the course of module teaching. Relatively, weak performing students tend to benefit more highly from formative assessments, leading to improvement of their overall success results, which in turn increases the overall pass rate for the module. Meanwhile, summative assessments comprising tests, examinations etc. are deemed to measure performance of students towards promotion or progression to the next level, or towards completion of study. As such, summative assessments are often associated with evaluation of cognitive abilities of students [8, 10].

COVID-19 pandemic lockdown has impacted education worldwide since 2019. In response, alternative technology-anchored educational approach(es) were rapidly enhanced or developed, and employed for learning and teaching by HEIs worldwide. Consequently since then, online teaching has taken centre-stage as the main alternative (at least temporarily) to the conventional contact face-to-face teaching and learning. Owing to the remote nature of learning under online teaching, assessments were also generally transitioned (at least temporarily) to continuous evaluation (CEv), as opposed to the conventional summative evaluation (SEv) approach. Table 1 outlines the differences between CEv and SEv as employed in South Africa. It can be seen in the table that, both approaches contain elements of both formative and summative assessment components but of different weightings, criteria or requirements. In the conventional SEv approach, a high weighting of at least 50% is typically assigned to end-of-

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Table 1. Comparison of summative and continuous evaluation approaches.

	Conventional summative evaluation (SEv)	Continuous evaluation (CEv)
1.	40% subminimum semester mark is required to qualify for end-of-module examination (EMA).	No subminimum required or involved.
2.	Re-write i.e. supplementary examination, is administered.	No re-write for students that fail the module.
3.	Number of assessments are fewer.	A larger number of assessment opportunities are administered.
4.	Higher weighting of 50–70% is allocated to EMA.	Smaller weightings are distributed across several assessment opportunities which may or may not include EMA.

module examination assessment (EMA) mark, while the CEv approach comprises a relatively larger number of assessment opportunities such as assignments, tests, tutorials etc., (Section 2.0) with smaller weightings assigned to each. The present paper, however, is based on data generated under the conventional SEv approach, as explained later in Section 3.0.

1.2 Objectives

A new model giving the mathematical relationship between formative and summative assessment results, was recently proposed in the associated paper [3]. In the present study, the new model was employed for probabilistic predictions to determine summative performance of engineering students, while also assessing the model's robustness and accuracy. Accordingly, data employed in the study contained several variables involving varied class sizes, heterogeneous classes with students of widely varying academic performance levels, different degree programmes comprising bachelors and masters study levels etc. The stochastic applicative approach was employed to evaluate the potential for practical application of the prediction method.

2. Measurement of Learning Outcomes

Most HEIs offering undergraduate and postgraduate engineering study programmes, utilize the different types of assessments shown in Fig. 1. Typically, *instruction process* assessments are conducted to satisfy quality assurance system requirements of the institution. Meanwhile, the success or failure of students in their modules or study programmes, is determined from *competence* i.e. formative and summative assessments, conducted by departments that host the particular study programme(s) offered.

Formative assessments are continuous evaluations on the learning acquired by students during the course of module delivery. In engineering disciplines for example, formative assessments typically involve various forms including assignments, practical work, experiments, class tests etc. These assessment components are conducted progressively at different stages of the module's teaching delivery, for purposes of enriching and evaluating students progress. *Summative* assessment typically comprises a final test or EMA. This high stakes test or examination is conducted to evaluate mastery of the knowledge attained by students, in relation to the module content delivered during the course of learning. Accordingly, summative assessment is typically structured to provide balanced coverage of the module content, rather than simply selecting sections or parts of it. Summative assessment marks are then integrated with formative assessment results, to determine the overall academic performance of a student. The foregoing process may be structured to follow the SEv or CEv approach, as earlier discussed (Section 1.1, Table 1).

Learning outcomes in engineering studies are typically pre-defined according to the accreditation requirements, governed by a national professional body. In South Africa for example, the Engineering Council of South Africa (ECSA) which is also a signatory to an International Accord recognizing engineering programmes in 17 different countries, places a demand on HEIs to ensure that students achieve the specified learning outcomes [11]. HEIs are therefore required to measure these learning outcomes based on evidence that demonstrates satisfactory attainment by students at exit level. In engineering studies, the required knowledge areas that must be taught and assessed comprise basic sciences, mathematical sciences, engineering sciences, engineering design and synthesis, as these form the core tenets of the discipline. Meanwhile, *generic* or transferable knowledge and skills (also referred to as soft skills) such as computing, information technology and other complementary subjects, are offered selectively at the discretion of HEIs and their departments.

At exit level, the competencies attained by students must be demonstrated. For example, students are required to satisfy the outcomes of core competency domains such as problem solving, applied scientific knowledge, engineering design, ability to conduct engineering procedures and investigations etc. In addition, students are also required to show satisfactory attainment of generic competencies which may include professionalism, technical communication, lifelong learning ability, teamwork abilities, and awareness of the impact of engineering in society [12]. Evidently, effective monitoring of the foregoing competencies requires that integrated formative and summative assessments, are conducted at different stages of learning. For example, the student's ability to conduct engineering procedures and methods, would be evaluated based on experiments and projects, while technical communication and/or teamwork would be assessed through writing of laboratory and project reports. These components fall under the formative assessment category. It should also be considered that students tend to direct their study efforts and commitments, in accordance with the type and value of assessment. High stakes assessments that contribute strongly to the overall grade, are generally taken more seriously and given greater commitment by students, relative to those that are assigned low weightings [1, 13–15].

Already it was mentioned earlier, that formative assessments typically consist of several components including assignments, laboratory projects, class tests etc., while summative assessment usually involves a single test or EMA event. For most South African engineering study programmes, the results of formative and summative assessments may contribute equally to the overall assessment mark (OAM) awarded to the student. Accordingly, the OAM mark is a composite of 50% formative assessment mark (FAM) plus 50% examination (EXAM) mark. It may be recalled that formative assessment is also a composite of sub-components comprising different weightings. For example, a FAM mark composite may comprise 5% assignment, 10% project report and 35% class test. In such a multifaceted assessment approach, students are compelled to direct their study efforts to both the formative and summative assessments, with some understanding of the implications associated with results that they obtain from each assessment component. Instructors also face the challenge of developing effective assessments that appropriately measure the learning outcomes. In the literatures, some attempts have been made to define some criteria that could be used to determine the effectiveness of assessments [16–19].

3. Data Characteristics

Data employed in the model's evaluation comprised four (4) civil engineering modules involving 441 students in seven (7) different examination events. The variables embedded in the data include the involvement of: (i) various undergraduate and postgraduate degree programmes, (ii) different engineering sub-disciplines and programmes comprising BEng in civil engineering and MEng in structural engineering, (iii) various class groups of small to large sizes ranging from 29 to 97 students, (iv) heterogeneous classes comprising students of different academic competencies, as indicated in Table 2 showing varying class average values of the FAM and OAM marks.

The present data are based on the SEv approach (Section 1.1), in which the OAM mark was calculated using fixed weightings of 50% FAM mark and 50% EMA examination mark (Table 1). In the present study, only the FAM and OAM results are of interest. As mentioned earlier, the FAM mark itself is a composite result determined from assignments, laboratory experiments, class tests etc., all of which are combined using weightings that are different for each module, as decided upon by the instructor(s). Table 2 is a summary of data employed in the present study, giving class averages of FAM and OAM marks for each of the examination events. The modules S4A18 and DAR18 gave the least and the best OAM results comprising class averages of 47.1% and 62.7%, respectively. As expected, FAM marks are relatively higher than

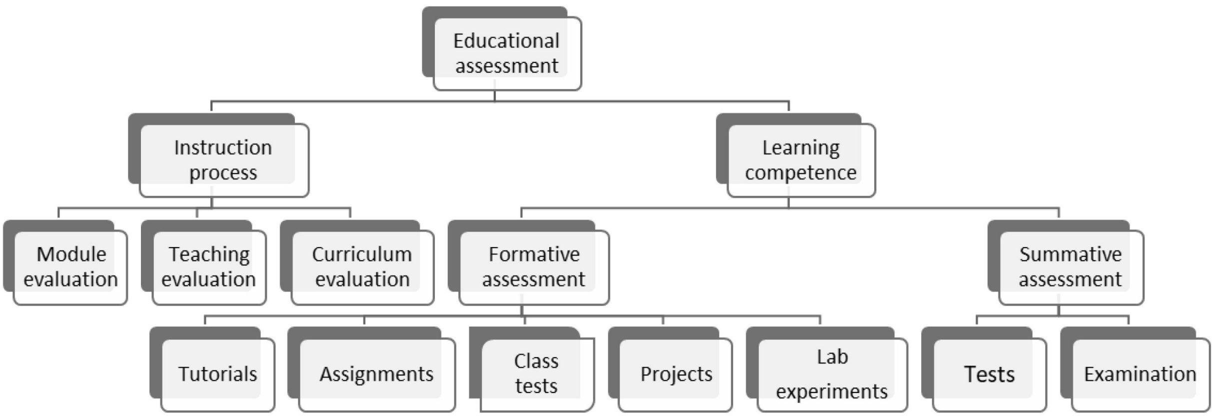

Fig. 1. Types of educational assessments at higher institutions of learning.

the corresponding OAM marks. However, the FAM and OAM marks show similar respective standard deviations of 10.1 and 9.3.

4. Prediction Model

Derivation of the new model given in equation below, is described in an earlier associated paper [3].

$$\mathrm{OAM} = P(\mathrm{FAM})^{Q}$$
$$\text{where } P = 3.2 \text{ and } Q = 0.7$$
$$\text{and } Q = 1.033P^{-0.347}$$

In the equation, P and Q are variables describing the data characteristics holistically associated with the module delivery and students learning experiences. Although these two variables may change depending on data characteristics, Ekolu [3] recommends using P = 3.2 and Q = 0.7 as starting values. Also given in [3] are different values of P and Q, that may be considered for modules of different data characteristics.

5. Comparison of Model's Prediction with Actual Results

The strong relationship between FAM and OAM marks forms the basis of the model's formula given in the foregoing section. It is emphasized that data used in the present study are independent of those that were employed in [3] for the model's derivation. For each module, the present study compares the model's predicted OAM results against actual OAM marks of the individual students, as shown in Fig. 2. It can be seen that for all modules, data points lie along the line of equality, thereby depicting statistical equality between the two sets of results. Considering the wide range of variables embedded in data characteristics, the model's demonstrated ability to correctly predict OAM results of individual students, is quite remarkable. Having observed the models prediction veracity, subsequent sections of this paper provide statistical evaluation of the model's accuracy and its potential for practical employment using the probabilistic applicative approach.

5.1 Statistical Error Analysis

The model's prediction performance was evaluated using various error indicators including the ratio of actual value (AV) of OAM to predicted value (PV) of the OAM mark i.e. AV/PV ratio, the root mean square of errors (RMS) and the coefficient of variation of errors (CV). Definitions for these parameters are already given in earlier works of the author [3, 20, 21] and are therefore not repeated here. For data of each module, the AV/PV ratio was calculated for each individual student. Considering the large data comprising 441 students, it is not convenient to present all the individual ratios in this paper, hence only the average ratio determined for each module, is given in Table 3. It can be seen that AV/PV values are between 0.95 to 1.09, indicating that the two sets of results are within the range of

Table 2. Assessment data of the various modules.

Module no.	Module name	Civil engineering degree	Class Size (No.)	FAM class average marks		OAM class average marks	
				Mark (%)	Std dev	Mark (%)	Std dev
1	S4A17	BEng	83	68.5	8.5	58.3	8.2
2	S4A18	BEng	74	52.6	11.3	47.1	8.1
3	S4A19	BEng	97	60.8	8.7	56.0	10.3
4	ACT18	MEng	62	59.1	9.5	59.3	10.6
5	DAR16	MEng	29	64.5	8.3	58.6	6.8
6	DAR18	MEng	33	63.0	13.3	62.7	10.4
7	ARCAD19	MEng	63	59.4	10.8	55.6	10.4
Global value			441	63.4	10.1	58.04	9.26

Table 3. Statistical error indicators of prediction accuracy

Module no.	Module name	Class size	Average AV/PV ratio	RMS	CV (%)
1	S4A17	83	0.95	6.7	11.4
2	S4A18	74	0.95	6.5	13.8
3	S4A19	97	0.99	7.9	14.2
4	ACT18	62	1.07	9.2	15.6
5	DAR16	29	0.99	3.8	6.5
6	DAR18	33	1.09	9.3	14.8
7	ARCAD19	63	1.0	6.6	12.0
Global value			1.01	5.0	8.83

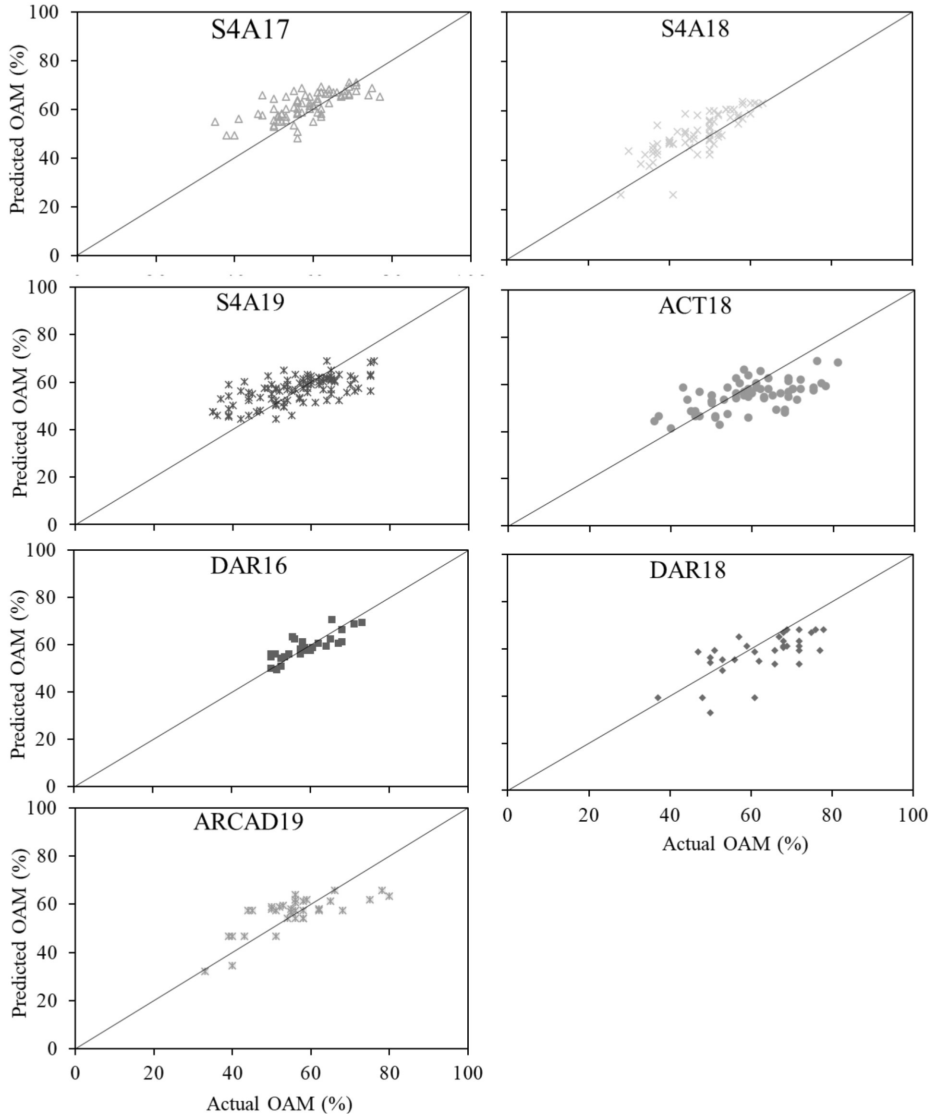

Fig. 2. Plots of actual OAM marks versus predicted OAM values: OAM – overall assessment mark.

perfect agreement which occurs at the ratio of 1.0. The observed accuracy of AV/PV values, also affirm the observations seen in the graphs of Fig. 2 showing strong correlations, with data values for each module consistently falling along the line of equality.

Typically in practice, a standard deviation of <5.0 or coefficient of variation <10%, indicates an excellent degree of control. A good degree of quality control is associated with a standard deviation of 5.0–7.0 or coefficient of variation of 10–15% [22]. The low RMS values of 4.0–9.0 obtained in the present study, indicate that the model exhibits good to excellent prediction performance. Similarly, the low CV values of 6–16% obtained, indicate that the model's predictions are of high accuracy. Recognized engineering code-type models typically give CV values of 20 to 45% [20, 23, 24]. Evidently, the model employed in the present study exhibits greater prediction accuracy than some well-established code-type models.

It is also interesting to note that class size influences the RMS value of results. Fig. 3 shows that RMS values generally increased with increase in class size. The trend seen in Fig. 3 appears to indicate that class groups of small, medium and large sizes may be categorized as those having 10–30, 31–70 and >70 students, respectively. Small to medium class sizes gave sporadic RMS values widely varying between 4.0–9.0. Further research is needed to investigate this observation. Meanwhile for large class sizes exceeding 70 students, the spread of RMS values becomes narrower with corresponding increase in class size. Overall, the RMS value converged towards 9.0 as class groups increased from small to large sizes.

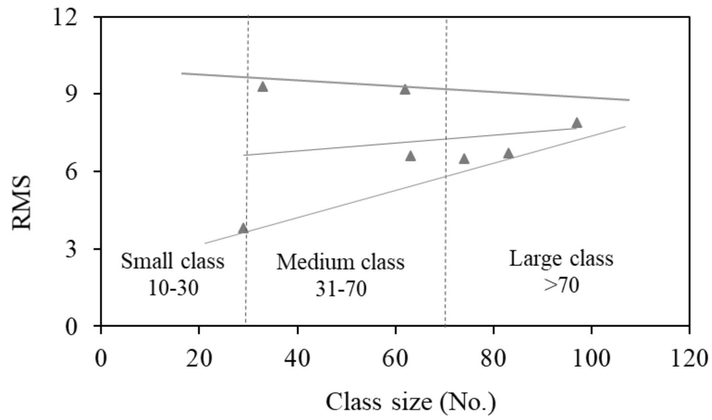

Fig. 3. Relationship between class size and root mean square of errors (RMS).

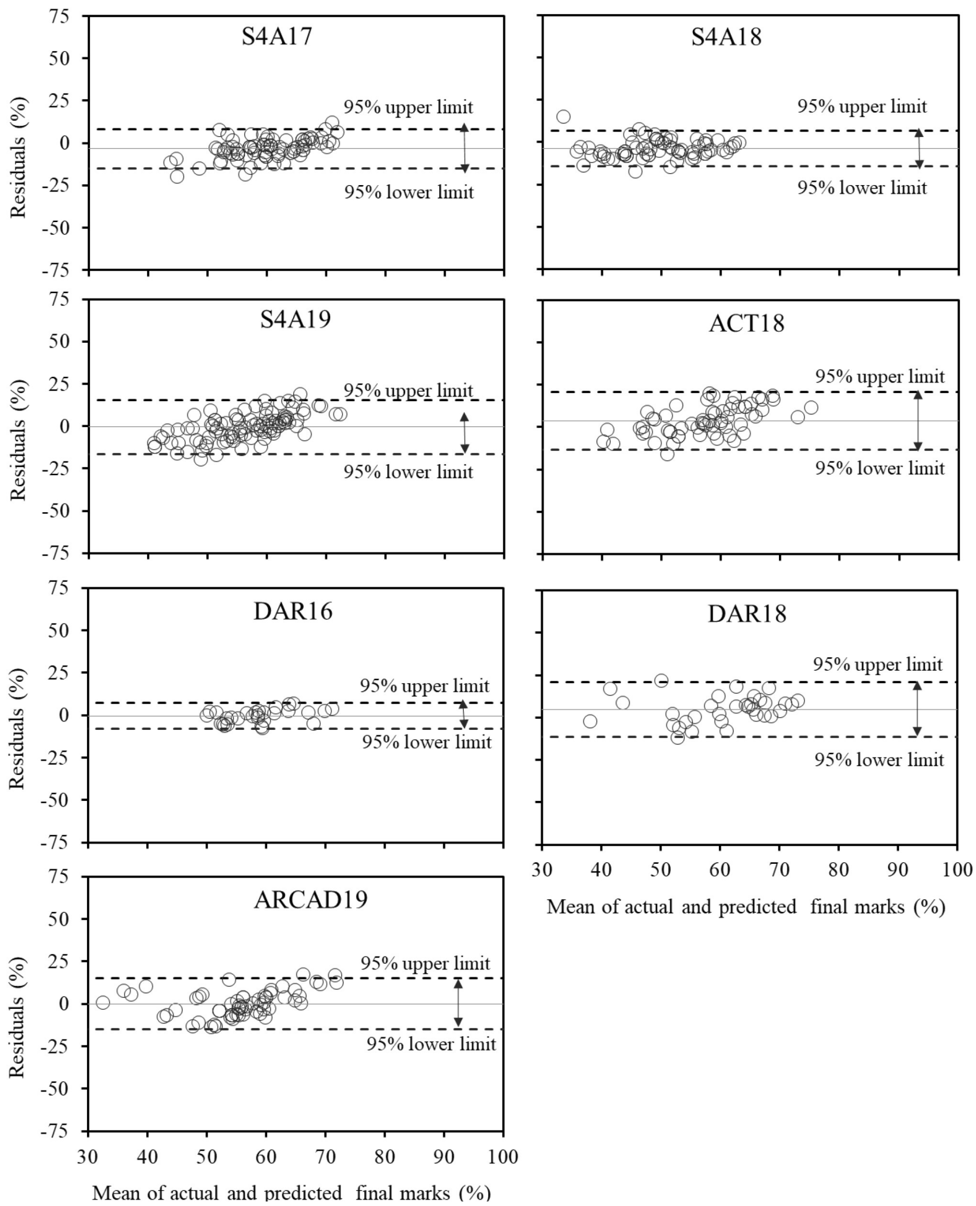

Fig. 4. Residuals between the predicted and actual OAM marks: OAM – overall assessment mark.

5.2 Residuals

Fig. 4 gives plots of residuals for the various randomly selected modules. Clearly, no heteroscedasticity tendencies such as convergence or fanning out occurred, as class size increased. Also shown in the graphs are limits for 95% confidence interval. Generally in all cases, the residuals fall within the 95% confidence limits. However, this interpretation is meaningful under the assumption that residuals exhibit the normal distribution characteristics. This presumption is indeed correct as seen in Fig. 5, showing that residuals for all the modules exhibited normal distribution curves.

5.3 Probabilistic Predictions

Variability is inherent in data of natural processes and systems. In order to account for variability of data in the model's predictions, the stochastic applicative method is the appropriate approach typically employed. Based on statistical error calculations shown in Table 3 and the criteria given in [22], the average RMS value of 7.0 was selected for use in probabilistic prediction calculations. To demonstrate stochastic application of the method, seven (7) data sets were randomly selected from various modules. The selection process was done randomly while ensuring that one data set is obtained from each module and that the selected OAM marks covered the full range of results from 40 to 90%. Marks below 40% were excluded since only students with a sub-minimum FAM mark exceeding this value, are usually allowed to take the EMA examinations. Also, values above 90% were excluded since such a high level of marks, is rarely achieved in engineering modules.

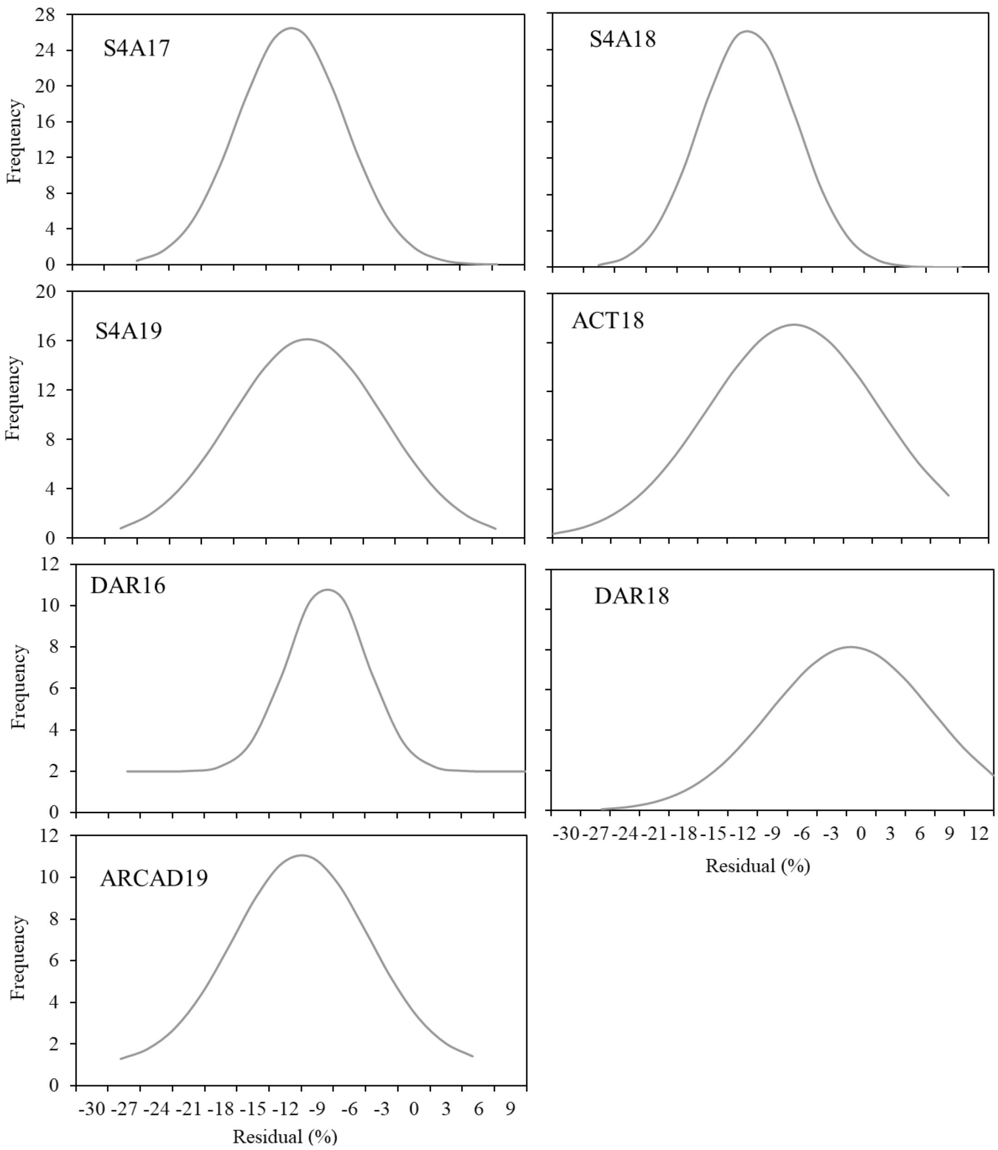

Fig. 5. Residuals exhibiting the normal distribution curve behaviour.

Table 4. Probabilistic predictions for overall assessment marks.

Data no.	Module name	Student name	FAM*	EXAM or EMA	Actual OAM	Predicted OAM	68.2% probability		86.6% probability		95% probability	
1	S4A17	BNN	61	44	53	56.9	50–64	√	46–67	√	39–67	√
2	S4A18	ZBOP	46	35	41	46.7	40–54	√	36–57	√	27–55	√
3	S4A19	DBP	58	31	45	54.9	48–62	X	44–65	√	31–59	√
4	ACT18	MSO	81	80	81	69.4	62–76	X	59–80	X	67–95	√
5	DAR16	LM	70	42	56	62.6	56–70	√	52–73	√	42–70	√
6	DAR18	SAJT	64	57	61	58.8	52–66	√	48–69	√	47–75	√
7	ARCAD19	ST	63	27	45	58.2	51–65	X	48–69	X	31–59	√

* FAM – formative assessment mark, OAM – overall assessment mark, EXAM is end-of-module examination (EMA) mark, √ – correct prediction, X – incorrect prediction.

Initially, the model's deterministic predictions were calculated. Then by applying 1.0, 1.5 and 2.0 standard deviations, each deterministic mark prediction was converted to a range of minimum and maximum values at the different probability levels of 68.2%, 86.6% and 95%, respectively. Table 4 gives results of the probabilistic predictions for the randomly selected data sets. The range of marks showing the minimum and maximum predicted OAM values, are given for each probability level. As expected, deterministic predictions did not give correct estimations of the actual OAM marks. Results show that probabilistic predictions generally gave correct estimates of OAM values at an accuracy that was dependent on the level of probability. At 68.2% probability, three (3) of the seven (7) predicted OAM results, were incorrect. At 86.6% probability, the number of incorrect predictions reduced to only two values. At 95% probability, all the model's predictions were correct. It may be noted that the values that were incorrectly predicted were either the very low or very high marks, basically falling at the tail ends of the bell distribution curve. Considering that all data of the OAM marks exhibited the normal distribution curve behaviour, tail ends of the curve represent quite a small group of students.

From a practical perspective, it is also essential to consider the spread or range of predictions. At 90 and 95% probability levels, the ±10.5% and ±15% range values of predictions, are too large to be of practical use. However, the range of ±7.0% for predictions at 68.2% probability, is reasonable enough for practical purposes. Interestingly for FAM values falling between 50 and 70%, the corresponding OAM marks were predicted by the model, at 68.2% probability with 100% accuracy.

6. Model's Applications, Limitations and Future Research

6.1 Applications

The proposed model can be used by instructors as a screening tool during compilation of marks. If for example during grading, the OAM marks obtained by several students are found to fall outside the predicted performance results, such an observation may be an indication of an anomaly. In such cases, the instructor may then take further steps, which may include checking the marked scripts, interrogation of issues that may have unfolded prior to the final examination etc. The model can also be a useful tool to foster students' preparation for summative assessment. Based on FAM results, students can be informed of their predicted performance in summative assessment. Such prior knowledge gives students an anticipatory frame of mind which can be employed as an informed scientific basis for setting performance goals.

Finally, the model can be embedded into a policy framework under different scenarios to enhance students learning and performance towards the promotion of throughput. The dropout rate for engineering programmes in South Africa is very high, being 56% while only 30% of students complete engineering programmes after five (5) years of study [25, 26]. Improvement of student's performance during engineering studies is therefore of high importance to stakeholders. The proposed model has the potential to improve student's performance, but it may only be effective once built into the policy framework of HEIs. It is possible for HEIs to enact a policy that allows establishment of a dedicated "student performance monitoring" unit within an organogram of the university. The role of such a unit would be to apply techniques such as the proposed model etc., in order to timeously identify weak performing students that may need appropriate interventions during the course of formative assessments. Proactive measures can then be determined and undertaken to support such students in improving performance during summative assessment(s) undertaken towards the end-of-module teaching delivery.

6.2 Limitations and Future Research

It was highlighted in Ekolu [3] (also Section 4.0) that data characteristics of modules may differ depending on factors that underlie their generation. The present study claims that when the model is employed under stochastic analysis, it is fully accurate for prediction of formative marks that fall within the range of 50 to 70%. However, this observation was based on limited data generated by one lecturer in one discipline i.e. civil engineering. However, the current research is ongoing and incremental. The earlier associated studies [3, 7] focussed on literature review, research justification and model development using a small set of data. Subsequently, the validation study presented in this paper involved several variables in a larger data set generated by one civil engineering lecturer (Section 3.0).

Further research is needed to evaluate the model's performance using data generated by several lecturers other than the model's developer. Moreover, such data should be sourced from other engineering disciplines including mechanical, electrical, industrial engineering etc., in addition to data of civil engineering modules. Also needed is a case study, to practically apply the model actively in real-time during the course of teaching and learning over the semester or year.

So far, the model has been validated using data that was generated based on the conventional SEv assessment approach (Sections 1.1, 3.0). With online teaching taking centre-stage due to the COVID-19 pandemic, there is need to investigate and determine whether or not, the model could also be employed under the CEv assessment approach.

7. Conclusions

A new model was employed to conduct probabilistic prediction of overall performance for civil engineering students, based on their formative assessment results. It was found that the model showed robustness under a wide range of variables. Statistical evaluation shows that overall performance results for students whose formative assessment marks fall between 50 and 70%, may be estimated at 68.2% probability with 100% accuracy. The new model may be employed under a policy framework towards promotion of students' performance and throughput.

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