then H_0 rejected and if $G < \chi^2{}_{(1-\alpha)(df)}$ then H_0 be accepted. Where α is the significant level specified, and $df = m - 1$ with m number of model parameters.

Wald Test

According to Hosmer and Lemeshow (1989; 2013), to test the significance of $\beta_i (i = 0,1,\ldots, p)$ parameters, the Wald test is used individually. The Wald test uses Z statistics, where this Z statistic follows the Raw Normal distribution. The Z statistics are:

$$Z = \frac{\beta_1}{SE(\beta_1)} \quad ; i = 0,1,\ldots, p \tag{10}$$

Where β_1 is the estimator for parameters (β_1) and $SE(\beta_1)$= estimator of standard error for the coefficient β_1. The Wald test hypothesis is $H_0 : \beta_i = 0$. With alternatives $H_1 : \beta_i \neq 0 \quad (i = 0,1,\ldots, p)$. The criteria used if $-Z_{\frac{1}{2}(1-\alpha)} < Z < Z_{\frac{1}{2}(1-\alpha)}$ then H_0 accepted and if $Z_{\frac{1}{2}(\alpha)} \leq Z \leq Z_{\frac{1}{2}(1-\alpha)}$ then H_0 rejected. Where $Z_{\frac{1}{2}(\alpha)}$ is the percentile of a standard normal distribution with level significance α.

Hosmer & Lemeshow Test

According to Hosmer and Lemeshow (1989; 2013), the Hosmer and Lemeshow test is known as the Logistic Regression Model compatibility test for data. The equation of this test is as follows:

$$C = \sum_{i=1}^{g} \frac{(o_i - n_i \bar{\pi}_i)^2}{n_i \bar{\pi}_i (1 - \bar{\pi}_i)} \tag{11}$$

The hypothesis used is as follows:

H_0 :there is no difference between the results of observations with the model used

H_1 :there is a difference between the results of observations with the model used

This Hosmer and Lemeshow test will follow the Chi-Square distribution with degrees of freedom $df = (g - 2)$. In general use $g = 10$. Test the criteria used, namely: H_0 rejected if $C > \chi^2{}_{(1-\alpha)(g)}$ and H_0 accepted if $C < \chi^2{}_{(1-\alpha)(g)}$. Where the α level of significance is determined.

R-Squared Test R^2

According to Hosmer and Lemeshow (1989; 2013), the value of R^2 in the Logistic Regression analysis shows the strong relationship between independent variables and free variables. For the value of R^2 it is:

$$R^2 = 1 - \exp\left[-\left(\frac{L^2}{n} \right) \right] \tag{12}$$

where: L = log Likelihood value of the model and n = amount of data. If $R^2 \to 1$, then the relationship between the independent variable and the dependent variable is strong and if $R^2 \to 0$ then the relationship is weak.

3. Results and Analysis

Data analysis is done in the manner as described in section 2.1. Before the data is carried out further, it is necessary to test the normality that applies to multivariate analysts. In the multivariate analysis the normality test aims to determine whether the data distribution is close to or follows a normal distribution. Data that has a pattern like a normal distribution is good data for multivariate analysis. Data normality test is done by using SPSS. Data can be used to estimate the parameters of a binary logistic model after data is normally distributed.

3.1 Results

The vector estimator $\beta = (\beta_{0,}\beta_1,\ldots,\beta_8)$ is determined using the parameter estimation of Binary Logistic Regression by maximizing the Likelihood function in equation (6). Estimates are performed using the Particle Swarm Optimization algorithm as described in section 2.4. Parameter estimation using Particle Swarm Optimization algorithm is done using Matlab, while for estimation and Standard Error (SE) value is do using SPSS. Parameter and Standrad Error estimation results are shown in Table 1.

Testing the significance aims to test parameter estimators that influence the dependency variable $\pi(X)$. Testing the significance aims to test parameter estimators that influence the dependency variable. To find out the significant factors on the model carried out by Wald test, namely to test the overall parameters to obtain the best value by minimizing several parameters. This step is done by matching a model that only contains significant variables. The test uses the (Z) ratio test that is using equation (10), with the hypothesis test used is $H_0 : \beta_i = 0$ with alternative $H_1 : \beta_i \neq 0 \quad (i = 0,1,\ldots,8)$. Used $\alpha = 0.05, Z_{\frac{1}{2}(0.05)} = -0.20$ and $Z_{\frac{1}{2}(0.05)} = 0.20$. Since $-0.27 \leq Z \leq 0.27$, it H_0 is accepted, and H_0 the others are rejected. The results are as follows:

Table 1. Significant Variable Parameter Estimates

Parameter Coefficient (X_i)	Parameter Estimator (β_i)	Standard Error $SE(\beta_i)$	Ratio (Z) $\frac{\beta_i}{SE(\beta_i)}$	Significance
Age (X_1)	-0.896069	0.974	-0.919988706	Signifikance
Family dependents (X_2)	-0.118182	0.415	-0.284775903	Signifikance
The amount of savings (X_3)	0.382378	0.650	0.588273846	Signifikance
The value of collateral (X_4)	2.083042	1.918	1.086049009	Signifikance
Given the credit limit (X_6)	-0.477245	2.045	-0.233371638	Signifikance
The loan term (X_8)	0.791815	0.646	1.225719814	Signifikance

Maximum Likelihood value $\hat{\beta} = 30.0000$

Then, the results obtained β_5 and β_7 are not significant. Because of parameter estimation β_5 and β_7 not significant, this parameter is removed from the model because the parameters do not significantly affect the model. Therefore, it is necessary to re-estimate the model without including β_5 and β_7 .

Based on the Wald test produced in Table 1, it can be seen that the factors that influence decision making significantly do not have a significant effect on the level $\alpha = 5\%$. The difference between the two models is Family dependents (X_5) and Take home pay (X_7) for the loan to be removed from the original model. The Likelihood ratio test that compares these two models is obtained using G definitions, which follow the Chi-Square distribution.

The re-estimation results of the Hosmer & Lemeshow Test aim to analyze the suitability of the Logistics model with data. The Hosmer & Lemeshow statistical test is done by equation (11). The hypothesis used is:

H_0 : observations with predictions of the same model

H_1 : observations with different model predictions

The Hosmer & Lemeshow statistical test uses equation (11) or uses statistics $P-Value$, the test criteria used, are H_0 rejected if $P-Value$ less than a significant level and H_0 accepted if $P-Value$ it is greater than the significant level. Significant level used is $\alpha = 0.05$. In this study, $P-Value$ obtained is 0.317, therefore $P-Value > \alpha$ and H_0 the hypothesis is accepted, which means "there is no difference between observation and model estimator".

The next step is to examine the relationship between independent variables and dependent variables based on R^2 values. This step follows equation (12) which is to produce a R^2 value of 0.94174283, which is obtained from re-estimation data that shows the relationship between independent variables, namely age, family dependence, amount of savings, collateral value, credit limit, and loan period, that dependence on variables $\pi(X)$ very significant probability. Thus, the estimated logistic regression based on re-estimation has the following equation:

$$\pi(X) = e^{3.00000-0.919988706X_1-0.284775903X_2+0.588273846X_3+1.086049009X_4=0.233371638X_6+1.225719814X_8}$$

The Logistic Regression equation above is a default problem obtained from debtor data in the opinion of the borrower credit.

3.2 Analysis

Credit worthiness decisions are made using risk prediction (valuation) by considering the probability of defaulting on the prospective debtor. Here are the credit risk titles:

Table 2. Predicate Credit Risk

Probability of default (Credit risk)	Predicate	Description
$0.00 < \pi(X) \leq 0.49$	A	Decent
$0.49 < \pi(X) \leq 0.69$	B	Pretty Decent
$0.69 < \pi(X) \leq 1.00$	C	Not Decent

The credit risk predicate above can be used to analyze credit in financial service cooperatives. The analysis of credit scoring aims to reduce the risk of default on prospective borrowers which results in losses for financial services. Therefore, financial service cooperatives to avoid losses must form a credit assessment model based on their own debtors.

4. Conclusion

The Particle Swarm Optimization algorithm is used as a Logistic Regression estimator with the aim of analyzing credit in financial service cooperatives. In this study, it was conducted on a financial service. It consists of eight factors analyzed, but there are six factors that influence significantly the probability of failure. Estimated probability of default is estimated by the logistic regression model, which is then matched with the loan feasibility interval to obtain the title of each prospective debtor. Based on the predicate obtained, the prospective debtor will obtain a decision from a financial service whether or not the prospective debtor is granted a loan.

Acknowledgements

Acknowledgments are conveyed to the Rector, Director of Directorate of Research, Community Involvement and Innovation, and the Dean of Faculty of Mathematics and Natural Sciences, Universitas Padjadjaran.

References

Agresti, A. (2002) Categorical Data Analysis, New York: John Wiley & Sons, Inc.,

Bekhet,H. A. Eletter, S. F. K.,(2014) Credit risk assessment model for Jordanian commercial banks: Neural scoring approach. Review of Development Finance. Vol 4, Pages 20–28. http://dx.doi.org/10.1016/j.rdf.2014.03.002

Czepiel, S.A. (2005). Maximum Likelihood Estimation of Logistic Regression. Models: Theory and Implementation, (On Line)

Dellien, H., Schreiner, M. (2005). Credit Scoring, Banks, and Microfinance: Balancing High-Tech with High-Touch, Working Paper, Women's World Banking, 8 West 40th Street, 9th Floor, New York, NY 10018, U.S.A.

Doblas-Madrid, A, & Minetti, R. (2013). Sharing information in the credit market: Contract-level evidence from US firms. Journal of financial Economics, Vol 109(1), Pages 198-223.

D. Zouache, et all (2015). Quantum-inspired firefly algorithm with particle swarm optimization for discrete optimization problems, Soft Computing Vol 20. Pages 2781–2799.

Fang, F., & Chen, Y, (2018). A New Approach for Credit Scoring by Directly Maximizing the Kolmogorov-Smirnov Statistic. Computational Statistic and Data Analysis Vol 133 (2), Pages 180-194

Feelders, A.J, (2000). Credit Scoring and Reject Inference With Mixture. Models, Working Paper, Tilburg University, The Netherlands, Copyright © 2000 John Wiley & Sons, Ltd.

Hosmer, D.W., Lemeshow, S, Sturdivant, R.X, (2013). Applied Logistic Regression. John Wiley & Sons. ISBN: 978-0-470-58247-3

Hosmer, D.W., Lemeshow, S, Applied Logistic Regression, Canada : John Wiley & Sons, Inc., (1989).

Jakubik, P. Moinescu, B, (2015). Assessing optimal credit growth for an emerging banking system, Economic Systems http://dx.doi.org/10.1016/j.ecosys.2015.01.004

Kusi, B. A, & Ansah-Adu, K, (2015). Credit Information Sharing and its Impact on Access to Bank Credit across Income Bracket Groupings. International Journal, Vol 4(4).

Kusi, B. A, Komla, E. Ansah-Adu, Kwadjo, (2017). Bank Credit Risk and Credit Information Sharing in Africa: Does Credit Information Sharing Institutions and Context Matter?.Research in International Business and Finance. http://dx.doi.org/10.1016/j.ribaf.2017.07.047.

Kiran, M. S.,(2017), Particle swarm optimization with a new update mechanism, Appl. Soft Comput. Vol 60, pages 670–678.

Montrenko, A., Strijov, V, Weber, G, (2014). Sample Size Determination for Logistic Regression. Journal of Computational and Applied Mathematics 255 (2014) 743–752. http://dx.doi.org/10.1016/j.cam.2013.06.031.

Qasim, O. S., Algamal, Z. Y (2018). Feature Selection Using Partisle Swarm Optimization-based Logistic Regression Model. Chemometrics and Intelligent Laboratory Systems 182 (2018) 41–46. https://doi.org/10.1016/j.chemolab.2018.08.016

Samreen, A & Farheen Batul Zaidi, (2012). Design and Development of Credit Scoring Model for the Commercial banks of Pakistan: Forecasting Crediworthiness of Individual Borrowers,International Journal of Business and Social Science, Vol 3 No 17.

Sohn, S. Y., Kim, H. D, & Yoon, J.H. (2016) Techonology Credit Scoring Model with Fuzzy Logistic Regression. Applied Soft Computing, 43 (2016) 150-158 http://dx.doi.org/10.1016/j.asoc.2016.02.025.

Sukono, Sholahuddin, A, Mamat, M, Prafidya, K, (2014). Credit Scoring for Cooperative of Financial Services Using Logistic Regression Estimated by Genetic Algorithm. Journal for Theory and Applications. Vol. 8, no. 1-4, 2014

Tan, Y. (2015). The impact of risk and competition on bank profitability in China. J. Int. Finance. Markets. Inst. Money. doi: 10.1016/j.intfin.2015.09.003

Turan, H. (2016). The Weighting of Factors Affecting Credit Risk in Banking. Istanbul Conference of Economics and Finance, Vol 38 pages 49 – 53.

Wang, D, Zhang, Z., Bai, R., Mao, (2017). A hybrid system with filter approach and multiple population genetic algorithm for feature selection in credit scoring, Journal of Computational and Applied Mathematics. http://dx.doi.org/10.1016/j.cam.2017.04.036.

Biographies

Ulfa Rahmani is a magister student in the Department of Mathematics, Faculty of Mathematics and Natural Sciences, Universitas Padjadjaran, the field of applied mathematics, with a field of actuarial science.

Sukono is a lecturer in the Department of Mathematics, Faculty of Mathematics and Natural Sciences, Universitas Padjadjaran. Currently serves as Head of Master's Program in Mathematics, the field of applied mathematics, with a field of concentration of financial mathematics and actuarial sciences.

Riaman is a lecturer in the Department of Mathematics, Faculty of Mathematics and Natural Sciences, Universitas Padjadjaran. Her research focuses on Statistics, with a field of Insurance Mathematics

Subiyanto is a lecturer in the Department of Marine Science, Faculty of Fishery and Marine Science, Universitas Padjadjaran. He received his Ph.D in School of Ocean Engineering from Universiti Malaysia Terengganu (UMT), Malaysia in 2017. His research focuses on applied mathematics, numerical analysis and computational science.

Abdul Talib Bon is a professor of Production and Operations Management in the Faculty of Technology Management and Business at the Universiti Tun Hussein Onn Malaysia since 1999. He has a PhD in Computer Science, which he obtained from the Universite de La Rochelle, France in the year 2008. His doctoral thesis was on topic Process Quality Improvement on Beltline Moulding Manufacturing. He studied Business Administration in the Universiti Kebangsaan Malaysia for which he was awarded the MBA in the year 1998. He’s bachelor degree and diploma in Mechanical Engineering which his obtained from the Universiti Teknologi Malaysia. He received his postgraduate certificate in Mechatronics and Robotics from Carlisle, United Kingdom in 1997. He had published more 150 International Proceedings and International Journals and 8 books. He is a member of MSORSM, IIF, IEOM, IIE, INFORMS, TAM and MIM.