HYBRID TECHNIQUE BETWEEN DESIGN OF EXPERIMENTS AND ARTIFICIAL NEURAL NETWORKS FOR RAINFALL-RUNOFF MODEL CALIBRATION METHOD

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HYBRID TECHNIQUE BETWEEN DESIGN OF EXPERIMENTS AND ARTIFICIAL NEURAL NETWORKS FOR RAINFALL-RUNOFF MODEL CALIBRATION METHOD

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ABSTRACT

Calibration is one of standard procedures to be conducted before the application of hydrology models. Some rainfall-runoff models have many model parameters which cause more difficulties and require longer time in the calibration processes. This paper illustrates the application of a proposed hybrid technique between Design of Experiments (DOE) and Artificial Neural Networks (ANN) for calibrating the parameters of rainfall-runoff models. The DOE is used to select the appropriate sample experiments based on the range of model parameters, and the ANN is used to optimize the value of model parameters. A Mock rainfall-runoff model was used to illustrate the application of the proposed technique. As the model has six model parameters, the model calibration requires 32 runs in the linear full factorial design experiments or 77 runs in the curvature full factorial design experiments. The error back-propagation technique (BP) was utilized in this approach to synthesize the suitable networks for reflecting the relationships between goodness-of-fit criterion, the sum of absolute errors as the inputs and model-parameters as the outputs. Standard statistical techniques of goodness of fit, such as the Nash-Sutcliffe Efficiency, NSE and the sum of absolute error, |E| were used to measure the differences between simulated and observed runoffs. Observed runoff and climatic data, including rainfall from 1990 to 2010 for the Babak River Basin in Lombok, Indonesia were used in the calibration process; while, data from 2011 to 2016 were used for verification of the model. The results indicate the proposed technique gave more accurate calibrated parameters than the trial-and-error method. In addition, the proposed method requires less time for model calibration. The application of the proposed technique is not limited for calibrating rainfall-runoff models; however, it can be used to calibrate any kind of mathematical models.

Key words: ANN, DOE, Calibration Method, and Rainfall-Runoff Model.

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1. INTRODUCTION

In water resource studies, hydrologists usually prefer using conceptual basin models to estimate runoffs based on rainfall and evapotranspiration inputs, what so called rainfall-runoff models. Evapotranspiration was calculated using the Modified Penman method (Allen, et al, 1996). Since rainfall and evapotranspiration data are available for such a longer period and more complete than runoff data. However, the models that usually have many parameters presenting the effect of specific characteristic of basin to the runoff productions cannot simply used to generate the simulated runoffs. Otherwise, the simulated runoffs will very different from the observed runoffs. Therefore, there have been many model calibration methods offered since the model calibration is necessary. Each method has such a benefit compared with another method.

Since many advanced computers have been used, operation time is not the main consideration anymore. However, modellers in a particular situation do not want to deal with many complicated methodologies or formulas. Recently, modellers are offered to use the beneficial of artificial neural network methods for many problem solutions regarding not dealing with many formulas or models.

Neural networks, the biological brain simulations can learn from experiences, not from programming. They are good at pattern recognition are fast, are tolerant of imperfect data, and do not need formulas or rules (DACS, 1992). Artificial neural networks are analogue computing devices that empirically relate sets of input and output variables in problems in which the relationships between the input and output are typically non-linear. The terminology sounds biological and the systems were developed to simulate biological neural function. Though effectively analogue computing devices they are usually implemented on digital computers by software.

Experimental designs or designs of experiments (DOE) are used as the initial process to effectively collect the sample data (Sulistiyono, 1999) before going to the main process of optimisation using an artificial neural network (ANN). The benefits of the DOE-ANN that are not served by other model calibration methods are (DACS, 1992; and Sulistiyono, 1999).

- The method can describe the effect of each parameter and the parameter interactions.
- The method can effectively collect the sample data.
- The method does not need additional complicated models or functions to achieve the optimum.
- Many software packages of artificial neural network are available to use.

2. METHODOLOGY

The proposed methodology is technically to fit the simulated to observed runoffs, which are measured using goodness-of-fit an objective function criterion. The iterative procedures of the DOE-ANN calibration follow 12 steps:

- Select the range of model-parameters,

- Arrange the designed experiments using DOE,
- Conduct the experiments and calculated the responses using the objective function,
- Put the responses as the input of the ANN process,
- Put the model-parameters as the outputs of the ANN process,
- Design the ANN architecture and the termination criteria,
- Train the ANN process and save the best ANN training file,
- Evaluate the process using standard statistical techniques, NSE, mean error, etc.
- Examine the results of ANN process and compare the data to ANN results,
- Set zero as a new input of ANN process,
- Run the ANN training file,
- Obtain the output results as the calibrated parameters.

2.1. Goodness of Fit Criteria for Model Calibration

In this paper, a goodness of fit test is used as a testing tool of calibration results. The goodness of fit compares results of simulation during calibration process to the observed data (McCuen et al., 2006; Lalozaee et al., 2013; and Mugume et al., 2016). The functions of goodness of fit are shown in Eq. (1) to Eq. (3).

$$\sum|E| = \sum_{i=1}^{n}|Q_s - Q_o| \tag{1}$$

Where: $\sum|E|$ is the sum of absolute errors or residuals, Q_s is the simulated monthly runoffs, and Q_o is the observed monthly runoffs. $\sum|E|$ measures the total experimental errors that occurs in the simulation. The smaller the value of the measure the better is the fit. This measurement is unbiased; therefore, a perfect match can be obtained accurately. That is when the value of the measure equals zero.

$$NSE = 1 - \frac{\sum_{i=1}^{n}(Q_O - Q_S)^2}{\sum_{i=1}^{n}(Q_O - \overline{Q_O})^2} \tag{2}$$

Where: NSE = The Nash-Sutcliffe Efficiency, Q_O = The Observed Monthly River Flows, Q_S = The Simulated Monthly River Flows. The measure is akin to the coefficient of determination used in regression analysis. Moreover, it emphasizes the ratio of the difference between observed and simulated data to the average of observed data. Therefore, a value of R^2 equals 1.0, does not imply a perfect match, it is only more robust than the absolute residuals to indicate a perfect linear association.

$$D_V = \frac{\sum_{i=1}^{n}|V_O - V_S|}{\sum_{i=1}^{n}V_O} \tag{3}$$

Where: D_V = The Deviation of the Runoff Volume, V_{ob} = The observed runoff volume, V_S = The simulated runoff volume. Dv measures the percentage of the total experimental errors to the total observed values. Although, D_V equals zero does not indicate a perfect match but more likely measuring the quantity of runoff volume. A smaller value of the measure indicates that the observed and simulated runoff volumes are similar in magnitude.

2.2. Design of Experiments (DOE)

The collection sample data must properly regard to the accurate predicting the properties of the real population. Hence, the number of sample data rapidly increases as the increase of the number of model parameters. Therefore, DOE is usefully offered to effectively screen and pre-analyse sample data by estimating effects of parameters and parameter interactions (Sulistiyono,1999).

DOE will create a set of experiments based on arranged parameters. The designs of DOE that are compared in this research are full two-level factorial and fractional two-level factorial designs (Myers and Montgomery, 1995). The full factorial designs produce 2^k experiments, while the fractional factorial designs produce 2^{k-p} experiments. Where k is the number of model parameters and p is the number of parameter reductions. However, the risk of losing information for effect estimation becomes higher when the less number of experiment designs are applied. The two levels considered arranging the experiments are the lowest and the highest levels of parameters. The effect of each parameter and parameter interaction to the experimental response is calculated using Eq. (4):

$$\text{Effect} = \frac{\text{Contrast}}{2^{k-1}} \tag{4}$$

Where contrast is the summation of the experimental response based on the plus-minus sign table (Montgomery, 1997) and k is the number of model parameters.

2.3. Artificial Neural Networks (ANN)

Neural networks are systems of information process that are non-algorithmic, non-digital and parallel. The systems consist of a number of simple, non-linear and highly interconnected computational elements called neurons. Neural networks are trained by repeatedly presenting examples to the network. Each example includes both inputs and outputs. In currently available software packages these artificial neurons are called "processing elements" and have many capabilities (DACS, 1992). By organizing neurons into different layers and connecting them with proper weights, networks that are capable of learning can be created. The physical connection of typical neural network is shown in Fig. 1.

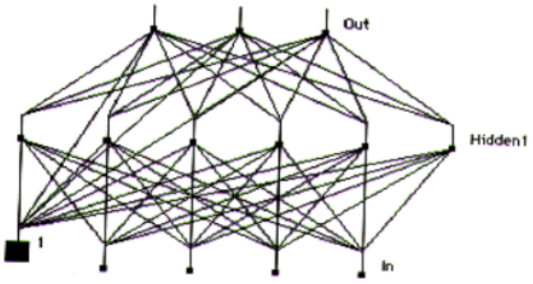

Figure 1 Typical Neural Network Architecture

Input information is modified and distributed sequentially to neurons of all layers. Final distribution is to mirror the last information equals to the outputs. This process runs repeatedly until the termination indicator obtains an optimum or a satisfied result. The modification in each neuron is based on selected weights. The all processes aim to reflect the relationship between inputs and outputs. Neural networks learn to solve problems without programming to do so but modifying the weights on the interconnections.

Typical processes of modifying and distributing information in the networks are technically to minimize the overall errors between inputs and outputs that mostly measured using the mean squared error, commonly called adaptive linear technique. If the actual output is compared to the desired outputs, then the error on the pattern calculated using Eq. (5) as

$$\text{Errors} = (\text{desired outputs}) - (\text{actual outputs}) \tag{5}$$

While, the weights on the input connections are adjusted using Eq. (6)

$$\bar{w} = \bar{w}_{old} + \frac{\beta E \bar{x}}{|x|^2} \tag{6}$$

Where $\bar{w}$ is the new weights, $\bar{w}_{old}$ is the old weights, β is the learning constant between 0 and 1, E is the errors, x is inputs, and $\bar{x}$ is the average of inputs.

This algorithm calculates the minimum of mean squares error for the collection of data pattern. Then these modified inputs are fed into the summing function. These operations produce a number of different values such as the average, the largest, and the smallest that are propagated forward. The output of the summing function is then sent into a transfer function. This function turns this number into a real output using an algorithm. It is this algorithm that takes the input and turns it into a zero or a one, a minus one or a one, or some other number. The transfer function that is commonly supported is sigmoid, as shown in Eq. (7) (Malik, 1993). The result of the transfer function is usually the direct output of the processing element. This sigmoid transfer function takes the value from the summation function, called sum in the Fig. 2, and turns it into a value between zero and one.

$$f(w) = \frac{1}{1 + e^{-w}} \tag{7}$$

Where: f(w) is the transfer function and w is the weighted input. The objective is either to minimize the value of f(w) as w approaches minus infinity is zero or to maximize the value of f(w) as w approaches plus infinity is one. It is clearly explained in Fig. 2.

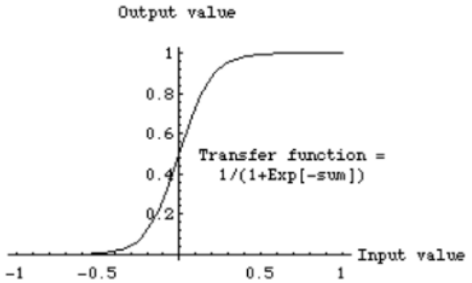

Figure 2 Sigmoid Transfer Function

The processing neuron finally output the result of its transfer function. This output is informed into other processing elements, or to an outside connection.

Backpropagation networks are known for their ability to generalize well on a wide-variety of problems. A backpropagation network is a supervised type of network, e.g., trained with both inputs and outputs. Depending upon the number of patterns, training may be slower than other paradigms. Backpropagation networks are used for the vast majority of working neural network applications because they tend to generalize well. When using Backpropagation networks, one can increase the precision of the network by creating a separate network for each output. Each layer connected to the immediately previous layer (with either 3, 4, or 5 layers). Using more than 3 layers is rarely necessary if one use NET-PERFECT. Using more than 5 layers should never be done because there is no known benefit to using more than 5 layers. NET-PERFECT is used to optimize the network by applying the current network to an independent test set during training. NET-PERFECT finds the optimum network for the data in the test set (which means that the network is able to generalize well and give good results on new data). NET-PERFECT does this by computing the mean squared error between actual and predicted for all outputs over all patterns. (The mean squared error is the standard statistical technique for determining closeness of fit.) NET-PERFECT computes the squared error for each output in a pattern, totals them and then computes the mean of that number over all patterns in the test set. Using statistical reports, R-squared, Mean Squared Error, Mean Absolute Error, Minimum Absolute Error, Maximum Absolute Error, and Linear Correlation Coefficient, one can analyze the learning progress of the network regarding to the errors. Moreover, R squared, the coefficient of multiple determination, is used to compare the accuracy of the model to the accuracy of a trivial benchmark model wherein the prediction is simply the mean of all of the samples. A perfect fit would result in an R squared value of 1, a very good fit near 1, and a very poor fit near 0.

A jump connection, a common type of backpropagation artificial neural network architecture which every layer is connected or linked to every previous layer is applied in this research. The number of layers in the connection can be a three, four, or five-layer network with jump connections. Learning rate, momentum, weight and links are the essential parameters in the ANN process. Each time a pattern is presented to the network, the weights leading to an output node are modified slightly during learning in the direction required to produce a smaller error the next time the same pattern is presented. The amount of weight modification is the learning rate times the error. For example, if the learning rate is .5, the weight change is one half the errors. The larger the learning rate, the larger the weight changes, and the faster the learning will proceed. Large learning rates often lead to oscillation of weight changes and learning never completes, or the model converges to a solution that is not optimal. One way that to allow faster learning without oscillation is to make the weight change a function of the previous weight change to provide a smoothing effect. The momentum factor determines the proportion of the last weight change that is added into the new weight change. As neurons pass values from one layer of the network to the next layer, the values are modified by a weight value in the link that represents connection strengths between the neurons. When the network is designed in the Architecture and Parameters module, the weights begin as random numbers that fall within a range specified in the module. As each pattern passes though the network, the weight is raised to positively reinforce a connection. To negatively reinforce or inhibit a connection, the weight is lowered. A link is the connection or set of weights between the slabs or groups of neurons in a network. Each link can have an individual learning rate and momentum, and one can set the weight range for the link in the Architecture and Parameters module.

There are two pattern selections, rotation and random, usually used in the ANN training process. Commonly, rotation pattern is used when like training patterns are dispersed evenly throughout the training set. While, random is used when the training set contains patterns that are cyclical (such as sales figures that follow seasonal variations) and you want the network to give answers independently of clustered data patterns. To terminate the ANN training process, some criteria must be obtained such as the average error is below a predefined level, the number of epochs since min equals to a certain number, the average error exceeds a specified number, the largest error is below a predefined level, and the learning epochs exceeds a predefined number.

3. APPLICATION

To demonstrate the procedure, data from the Babak river basin in Lombok Island, Indonesia are used to demonstrate the application of the proposed calibration method. The basin covers an area of 286 km^2, approximately five percent of the whole island. It is the largest basin in the island. According to the Irrigation Plan Development, the Land Use of Babak river basin in 1985 includes 35 %, 28 %, 32 %, and 5 % of horticulture, paddy fields, forest, and villages, respectively (Kadarisman, 1993). To simplify the investigation of the water availability from the basin to supply the demand for water, the Government Agencies have used the Mock Rainfall-Runoff model to generate simulated runoffs based on observed rainfalls and evapotranspiration inputs, since the records of rainfalls and evapotranspiration are available for a much longer than the record of runoffs. Therefore, the Mock model that has six parameters must be calibrated to produce accurate results.

The Mock Rainfall-Runoff Model which has six parameters (Mock, 1973) together with data from the Babak River Basin in Lombok, Indonesia will be used to illustrate the application of the RSM. The six parameters are: impermeable layer (A), initial storage (B), coefficient of infiltration (C), coefficient of recession (D), soil moisture capacity (E), and initial soil moisture (F) have ranges: 0.08 ~ 0.12, 150 ~ 250, 0.35 ~ 0.65, 0.6 ~ 0.8, 180 ~ 220, and 190 ~ 210, respectively (Sulistiyono,1999). The inputs to the model are observed rainfall and evapotranspiration data from 1990 – 2010, and the observed runoff from the same period will be used in the calibration are shown in the Figure 1. The optimum responses will be reached by minimizing Residuals and Dv, maximizing NSE, and obtaining a |E| as close to zero as possible. The result of the calibration was then verified using observed rainfall and runoff data from 2011 – 2016.

4. RESULTS AND DISCUSSION

As shown in Table 1, among the 63 factor effects, the main parameters B, C, D, and E have high effects on the response. The first and the second highest effect parameters are C (Coefficient of Infiltration) and D (Recession constant), respectively. For two-parameter interactions, BC, AD, BD, CD, BE, CE, and DE are considered to have high effects. According to the results of effect estimation, to increase the responses, parameters and parameter-interactions that have positive effect must be increased and parameters and parameter-interactions that have negative effect must be decreased.

Table 1 The Effect Estimation based on the response of absolute residuals calculated using FF and OHF Designs

Parameter& interactions	Effects	
	Full	OHF
A	0.978906	1.288438
B	26.17097	26.16119
AB	0.589781	0.701437
C	228.1398	228.1407
AC	0.589781	0.701437
BC	-10.7546	-10.7456
ABC	-2.52078	-3.34631
D	-83.6533	-83.6552
AD	9.903281	9.865063
BD	-16.9645	-16.9744
ABD	0.828156	0.829062
CD	318.0513	318.0526
ACD	0.828156	0.829062
BCD	0.009559	=AEF
ABCD	-0.69591	=EF
E	66.30784	66.30631
AE	-1.04122	-0.73169
BE	-27.2814	-27.2912
ABE	-0.32909	-0.21744
CE	-13.8896	-13.8887
ACE	-0.32909	-0.21744
BCE	8.697781	=ADF
ABCE	-0.83447	=DF
DE	22.72134	22.71944
ADE	0.755906	0.717687
BDE	16.60334	=ACF
ABDE	-0.56697	=CF
CDE	-1.05853	=ABF
ACDE	-1.00328	=BF
BCDE	3.831531	=AF
ABCDE	0.433219	=F
F	-3.72828	-3.29506
AF	0.009406	-1.28844
BF	1.031469	-26.1612
ABF	0.001281	-0.70144
CF	1.200906	-1.22101
ACF	-15.45996	-15.4227
BCF	-0.03822	=ADE
ABCF	-0.00191	=DE
DF	-0.82553	-0.83655
ADF	9.03114	9.86506
BDF	-0.56403	=ACE
ABDF	0.000906	=CE
CDF	0.111656	=ABE
ACDF	0.000906	=BE
BCDF	0.309531	=AE
ABCDF	-0.00153	=E
EF	-3.72828	-3.63063
AEF	0.009406	0.731687
BEF	1.031469	=ACD
ABEF	0.001281	=CD
CEF	1.200906	=ABD
ACEF	0.001281	=BD
BCEF	-0.03822	=AD
ABCEF	-0.00191	=D
DEF	-0.82553	=ABC
ADEF	0.009031	=BC
BDEF	-0.56403	=AC
ABDEF	0.000906	=C
CDEF	0.111656	=AB
ACDEF	-0.00978	=B
BCDEF	0.309531	=A
ABCDEF	-0.00153	=I

Effects of parameters and their interactions can also be clearly distinguished using a normal plot view shown in Fig. 3.

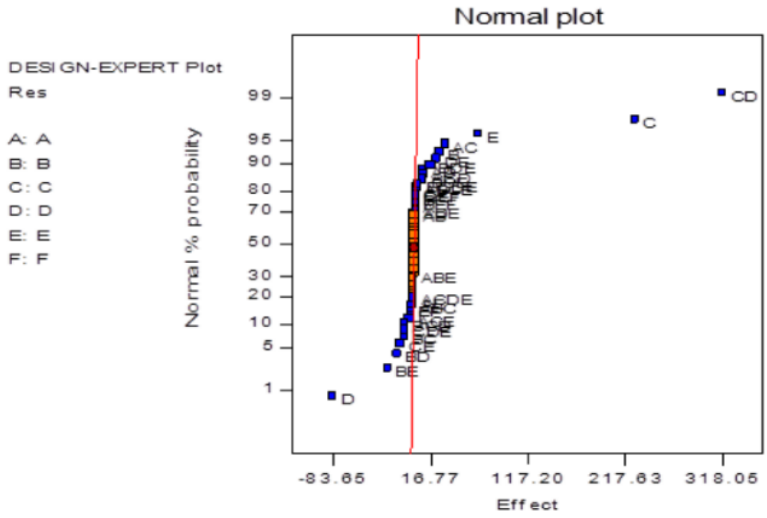

Figure 3 The Normal Plot of Effects

Fig. 1 shows parameters C, D, E, and interaction CD lying far away from the normal line. Parameters C, D, E, and interaction CD are considered to have high effects to the process. Therefore, at least C, D, E, and CD must be considered to involve in the polynomial model.

Table 2 The Calibrated Parameters of Mock model using ANN.

A	B	C	D	E	F
0.10	203.80	0.50	0.70	199.99	200.99

Table 2 shows the calibrated parameters of the Mock model for the Babak river basin. The calibrated parameters must be set back to the Mock model to prove that the calibrated parameters can produce simulated runoffs similar to observed runoffs. The comparison between simulated and observed runoffs can be shown through the plot in Fig. 4.

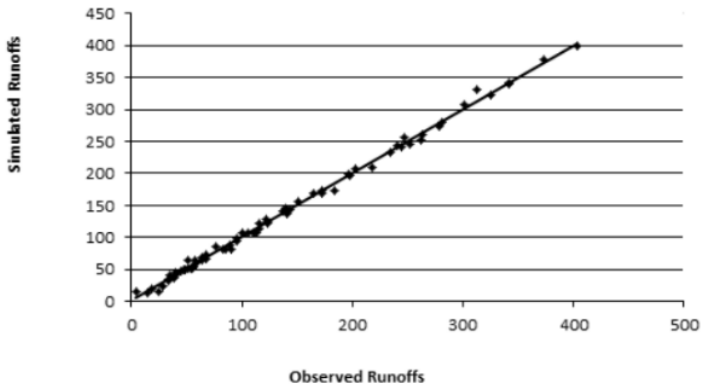

Figure 4 The Plot of Simulated and Observed Runoffs

Fig. 4 shows that the differences between simulated and observed runoffs are very small. It is also proved by the R-squared = 0.987 states that the line is linear in the significant of 5 %, which r(64) = 0.981. The linearity of the line states that simulated points are very similar to observed points. This similarity is also shown in the plot of monthly observed and simulated runoffs as shown in Fig. 5.

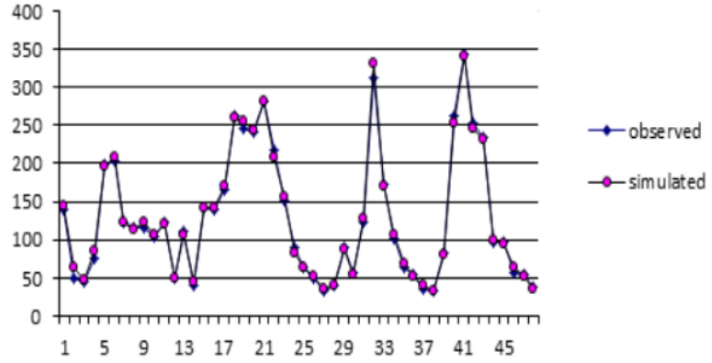

Figure 5 Observed and Simulated Runoffs

5. CONCLUSIONS

According to the results of calibration using DOE-ANN, factors B, C, E, A^2, C^2, D^2, AC, and CD have high positive effects on the response of the model. While, D, F, F^2, BE have high negative effects on the response of the model. It means that to optimise the response of the process, for example: to reduce the absolute sum of errors, modellers have to decrease parameters and interactions that have positive effects and to increase parameters and interactions that have negative effects.

In case of having single-parameters have the opposite effects from quadratic-parameters or their interactions, the priorities are to reduce the single-parameter that has the highest of positive effect and increase the single-parameter that has the highest of negative effect. Therefore, the parameters, which are considered as the priorities to optimise the process, are recognised.

In this study, for these particular data, the single-parameters, which affect very much the change of the Mock model's process are: Coefficient of Infiltration (COI) coded as C, Coefficient of Recession (K) coded as D, and Soil Moisture Capacity (SMC) coded as E. While, only interaction CD highly affects to the Mock model process. In addition, the calibrated parameters can be significantly used to simulated runoffs of the Babak River.

5. ACKNOWLEDGEMENTS

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PAGE 1

PAGE 2

PAGE 3

PAGE 4

PAGE 5

PAGE 6

PAGE 7

PAGE 8

PAGE 9

PAGE 10

PAGE 11